# Is Discrimination Due to a Coordination Failure? 

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#### Abstract

Can groups with equal productive potential end up in equilibria in which they get different average wages? In this paper we consider a simple model of statistical discrimination that shows that this might be the case. Discrimination in this model is possible because of the existence of multiple equilibria. We consider what determines whether such multiplicity is possible, what types of policies might be used to eliminate discrimination in this situation and, finally, we test the main hypothesis of this model, namely, that identical groups will be treated equally. Our empirical results suggest, however, that discrimination is more due to structural differences in the wage setting schedules faced by black and white males than to a coordination failure caused by statistical discrimination.


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## 1 Introduction

The purpose of this paper is twofold. In the first part we extend Lundberg and Starz' (1983) -L\&S- model of statistical discrimination to illustrate the differences between the case in which discrimination is caused by underlying differences between groups or the market conditions they face and the case in which discrimination is the consequence of a coordination failure even if the fundamental parameters of the model are symmetrical with respect to race. In particular, we will show how the qualitative properties of these two types of equilibria are essentially different, which has important implications for the effectiveness of possible affirmative action policies. In the second part of the paper, we test whether discrimination is caused by a coordination failure and show that the empirical evidence is at odds with the implications of the theoretical model.

Although many theories on labor market discrimination, e.g. Becker (1957, 1972), have emphasized the possible differences in market conditions and productive potential that might lead some groups to get different wages than others, there is also a branch in the literature that considers the possibility of discrimination being caused by the existence of multiple equilibria and possible self fulfilling stereotypes, like for example Arrow (1972a, b, 1973), Coate and Loury (1993), Kremer (1993), and more recently, Moro and Norman (1996) and Moro (1998). Discrimination as a result of a coordination failure in which one group ends up in a low productivity - low wage equilibrium and the other in a high productivity - high wage equilibrium is theoretically a very appealing scenario. This because it does not require any assumptions on why and how groups, like various ethnic groups or men and women, are different in their productive potential or the market conditions they face. Instead, the coordination failure theory of discrimination illustrates how, in principle, identical groups can adopt different strategies in equilibrium.

It was Becker (1957) who initiated the discussion on the economics of discrimination. His premise was that employers discriminated in the sense that they had a distaste for workers from certain groups, making them willing to make a financial sacrifice in order to hire workers of the preferred type. This kind of taste discrimination will ultimately lead to the discriminated group getting lower wages than the others. Becker's approach has been criticized mainly on the basis of two arguments. The first is that it breaks with the assumption that firms are profit maximizers and instead assumes that firms
are utility maximizing entities. This makes welfare comparisons in taste discrimination models virtually impossible. The second is that Becker fails to explain how the taste discrimination that he assumes can persist in perfectly competitive markets. In particular, if there are firms in the market that do not discriminate against blacks, there would be no discrimination in the long run.

In order to overcome these disadvantages of Becker's theory, Phelps (1972) and Arrow (1973) considered the possibility of discrimination as a result of an imperfection in the labor market. In particular, they considered models in which employers receive an imperfect signal about the productivity of their prospective employees. In that case, Phelps (1972) and Arrow (1973) show that employers have the incentive to judge the job applicants not only on the basis of their personal merits but also on the characteristics of the group that they belong to. There is, however, a major difference between Phelps' and Arrows' analyses.

Phelps shows that when blacks send a more noisy signal than whites, they will be judged more on the basis of their group characteristics than whites, and therefore, will have a lower return to their individual investment in education. This would eventually lead to blacks investing less in education than whites and thus getting lower average wages than whites. His analysis though, does not motivate any potential explanation by which the labor market signal of blacks would be more noisy than that of whites. Arrow shows that even when two groups are completely identical, i.e. both in their productive potential as well as in the reliability of their labor market signal, it might actually be the existence of multiple equilibria that leads to one group ending up in a low wage-low productivity equilibrium and the other in a high wage-high productivity equilibrium. In particular, the existence of multiple equilibria allows for the existence of self-fulfilling stereotypes. That is, if, for some reason, employers expect that black workers are less productive than white workers this might lower the incentive for black workers to invest in their human capital and eventually lead black workers to end up being less productive than whites.

Our model is a generalization of that considered by Lundberg (1991) and L\&S. We will show how the model can yield similar results as those presented by Arrow (1973), namely, it will lead to the possible existence of multiple equilibria in the case when two groups are completely identical. Though the same result, the mechanisms underlying it are different in our model. In particular, we couple Phelps' bayesian inference by employers of workers'
qualifications with Arrow's imperfect capital markets assumption to get our result. This way, we do not assume any cost of screening workers, as it is necessary in Arrow's model to get multiple equilibria.

The statistical discrimination model introduced in this paper is the first with possible multiple equilibria in which agents have a convex choice set for their human capital investment and in which the technology does not exhibit any complementarities. That is, in Arrow (1973), Coate and Loury (1993), Moro and Norman (1996) and Moro (1998) agents can only choose to be either skilled or unskilled while in the model introduced here agents can choose a continuum of education levels. Furthermore, a skill complementarity in the O-ring technology considered by Kremer (1993) implies that the marginal productivity of a worker and thus his incentive to invest in human capital is increasing in the average productivity level of the workers with whom he is matched. Finally, though Lundberg (1991) and L\&S do use both a continuum of education levels and their models do not exhibit complementarities, their model fails to generate the multiplicity of equilibria. Similar to Arrow (1973) and Coate and Loury (1993), externalities in the production technology do not play any role in the generation of multiple equilibria in our model, as they do in Moro and Norman (1996) and Moro (1998).

The structure of the paper is as follows. In Section 2 we will introduce the basic model of statistical discrimination that we will use in the rest of the paper. In Section 3 we will consider the two cases of possible equilibria of this model for various combinations of parameter values and identify when a strategic complementarity can lead to the existence of multiple equilibria. In Section 4 we will test the main implication that distinguishes the models that explain discrimination as a coordination failure due to multiple equilibria from the rest of the theories on discrimination. This null hypothesis is that if groups were identical in their human capital distributions then they would face equal wage schedules. This null hypothesis is tested using an extension of the standard wage equation in which the $\log$ of the (hourly) wages is considered a function of (potential) experience and education. Our results suggest that, contrary to the coordination failure theory of discrimination which predicts that wage differences between groups can be fully explained by differences in their human capital distributions, if one takes into account the human capital distributions non-statistical discrimination seems to be more severe than when one does not.

## 2 A simple model of statistical discrimination

We will use the following simple model of statistical discrimination to illustrate the various possible causes of strategic complementarities that might result in the existence of multiple equilibria. The model is a generalization of L\&S. It consists of two periods. In the first period prospective employees choose their level of investment in education. In the second period employers, that do not observe the employees' marginal productivity of labor, observe an imperfect labor market signal for each prospective employee and use it to make them a wage offer. Due to competitiveness of the labor market this wage offer will be such that the firm's expected profits will equal zero. More importantly, the expected wage offer will be a weighted average of the individual's productivity level and that of the group he or she belongs to.

There is a continuum of agents on the interval $[0,1]$, indexed by $i$, that all inelastically supply one unit of labor, i.e. $L_{i}=1$. Their individual output level depends on their human capital, or rather productivity, level, denoted by $h_{i}$. That is, total output equals

$$
Y=\int_{0}^{1} h_{i} L_{i} d i=\int_{0}^{1} h_{i} d i
$$

The labor market is competitive. Hence, in the case of perfect information this would simply lead to every individual getting a wage equal to her marginal product of labor, $h_{i}$. However, we will assume that person $i$ 's exact human capital level is not known to the employer. Instead, the firm gets an imperfect labor market signal, $T_{i}$, of the form

$$
T_{i}=h_{i}+\varepsilon_{i}
$$

where $\varepsilon_{i} \sim \operatorname{iid}\left(0, \sigma_{\varepsilon}\right)$ and the distributions of $h_{i}$ and $\varepsilon_{i}$ are common knowledge to both the firms and the workers. From the competitiveness of the labor market it follows that the firms will set the wages, $w_{i}$, such that

$$
w_{i}=E\left[h_{i} \mid T_{i}\right]
$$

This is a simple signal extraction problem. It can be easily seen that rational expectations imply that the resulting wage setting schedule is a weighted average of the signal and the mean human capital level, i.e.

$$
\begin{equation*}
w_{i}\left(h_{i}, \bar{h}\right)=\beta T_{i}+(1-\beta) \bar{h}=\beta h_{i}+(1-\beta) \bar{h}+\beta \varepsilon_{i} \tag{1}
\end{equation*}
$$

where the weight $\beta$ depends on the signal to noise ratio $\frac{\sigma_{h}^{2}}{\sigma_{\varepsilon}^{2}}$, such that

$$
\beta=\frac{\sigma_{h}^{2}}{\sigma_{h}^{2}+\sigma_{\varepsilon}^{2}}
$$

The individuals' educational expenses, $e_{i}$, determine her productivity level through the "schooling"-technology

$$
h_{i}=S_{i}\left(e_{i}\right)
$$

where, for all $i, S_{i}: \Re_{+} \rightarrow \Re_{+}$is assumed to be strictly concave and to satisfy the following Inada-type conditions: $\lim _{e_{i} \downarrow 0} S_{i}^{\prime}\left(e_{i}\right)=\infty$ and $\lim _{e_{i} \uparrow \infty} S_{i}^{\prime}\left(e_{i}\right)=0$. Following L\&S and Kremer (1993), we will assume that employees choose their education level, $e_{i}$ to maximize their expected net wage. That is, employees choose their investment in education according to

$$
e_{i}=\underset{e \in \Re_{+}}{\arg \max } E\left[w_{i}\left(S_{i}(e), \bar{h}\right)-e\right]
$$

which results in the following necessary and sufficient condition

$$
\begin{equation*}
\beta S_{i}^{\prime}\left(e_{i}\right)=1 \tag{2}
\end{equation*}
$$

The latter implies that the marginal revenue of education equals its marginal cost. In order to make the results in the rest of the paper tractable, we will assume that the schooling function is concave and of the following form ${ }^{1}$

$$
S_{i}\left(e_{i}\right)=\frac{a_{i}}{\gamma^{\gamma}} e_{i}^{\gamma}+b_{i}
$$

where $\gamma \in(0,1)$ and $a_{i}$ and $b_{i}$ are independent ${ }^{2}$ random variables that represent the persons marginal ability to learn and initial productivity level respectively. Including a random component which affects workers marginal ability to learn is the key element which differences this model from that of L\&S, and as will become clear shortly, is crucial in the generation of multiple

[^1]equilibria in the model. In order to get the equilibrium results of Section 4 using the simplest setup we will assume that $\operatorname{Ln}\left(a_{i}\right) \sim N\left(\mu_{a}, \sigma_{a}\right)$. Furthermore, $b_{i} \sim i i d\left(\mu_{b}, \sigma_{b}\right)$. Using this these assumptions, we obtain that
$$
S_{i}^{\prime}\left(e_{i}\right)=a_{i} \gamma^{1-\gamma} e_{i}^{\gamma-1}
$$

Under full-information, in equilibrium every worker will get a level of productivity and schooling $h^{f}=S^{f}=a^{1 /(1-\gamma)}+b$, by investing $e^{f}=\gamma a^{1 /(1-\gamma)}$. The per capita net social product of the investment in education is $S^{f}-e^{f}-$ $S(0)=(1-\gamma) a^{1 /(1-\gamma)}$.

On the other hand, under imperfect information, i.e., when workers face wage schedule (1), workers invest $e=\gamma(\beta a)^{1 /(1-\gamma)}$ to get a level of productivity

$$
h_{i}=a_{i}^{\frac{1}{1-\gamma}} \beta^{\frac{\gamma}{1-\gamma}}+b_{i}
$$

Notice that in this case, contrary to the model of L\&S, the amount invested in schooling is stochastic. While in their model all workers obtain the same amount of education and correspondingly, productivity, in this paper workers' heterogeneity leads to differences in education levels, and to a distribution of productivity levels.

The per capita net social product of the investment in education in this case is increasing monotonically in $\beta$, and is given by $S-e-S(0)=$ $(1-\beta \gamma)(\beta a)^{1 /(1-\gamma)}$.

That is, under imperfect information workers invest less, getting to an equilibrium with a lower productivity and a lower net social product of the investment in education.

Using the assumed log-normality of $a_{i}$ we find that

$$
\bar{h}=E\left[h_{i}\right]=\tilde{\mu}_{a} \beta^{\frac{\gamma}{1-\gamma}}+\mu_{b}
$$

and

$$
\sigma_{h}^{2}=\operatorname{Var}\left[h_{i}\right]=\tilde{\sigma}_{a}^{2} \beta^{\frac{2 \gamma}{1-\gamma}}+\sigma_{b}^{2}
$$

where $\widetilde{\mu}_{a}=E\left[a^{\frac{1}{1-\gamma}}\right]=e^{\frac{1}{1-\gamma} \mu_{a}+\frac{1}{2(1-\gamma)^{2}} \sigma_{a}^{2}}$ and $\tilde{\sigma}_{a}^{2}=\operatorname{Var}\left[a^{\frac{1}{1-\gamma}}\right]=e^{\frac{2}{1-\gamma} \mu_{a}+\frac{2}{(1-\gamma)^{2}} \sigma_{a}^{2}}-$ $e^{\frac{2}{1-\gamma} \mu_{a}+\frac{1}{(1-\gamma)^{2}}} \sigma_{a}^{2}$. Throughout the paper we will only consider pure strategy

Nash equilibria in the first period of the game ${ }^{3}$. In that case an equilibrium is characterized by a $\widehat{\beta}$ that is a fixed point of the function $f:[0,1] \rightarrow[0,1]$, such that

$$
\begin{equation*}
f(\beta)=\frac{\beta^{\frac{2 \gamma}{1-\gamma}}+\frac{\sigma_{b}^{2}}{\widetilde{\sigma}_{a}^{2}}}{\beta^{\frac{2 \gamma}{1-\gamma}}+\frac{\sigma_{b}^{2}}{\widetilde{\sigma}_{a}^{2}}+\frac{\sigma_{\varepsilon}^{2}}{\widetilde{\sigma}_{a}^{2}}} \tag{3}
\end{equation*}
$$

Notice that this equation for $\beta$ would be the same equation (10) in L\&S if we had not introduced heterogeneity in the innate marginal ability to learn of workers. That subtle assumption is what allows $\beta$ to appear in the right hand side of the equation as an additional component of the variance of the productivity level in the population.

In the following section we will use this condition to illustrate two types of equilibria considered in the literature. But before considering several types of equilibria we first notice that it follows immediately from Brouwer's fixed point theorem that the function $f$, as defined in 3 has at least one fixed point.

## 3 Discriminatory equilibria

In this section we will introduce two types of equilibrium outcomes of the model introduced above. The first is in the spirit of Phelps (1972) and L\&S and assumes that different groups obtain different equilibrium outcomes because they basically face different market conditions. In particular, just like in Phelps (1972) and L\&S, it is assumed that one group sends a less reliable labor market signal than the other. The second is what we denote as the coordination failure theory of discrimination, and follows Arrow (1973) and Coate and Loury (1993). It assumes that both groups face identical market conditions but that the existence of multiple equilibria allows for self-fulfilling stereotypes. We will show what types of externalities cause these multiple equilibria, argue why it would be possible for groups to end up in different equilibria and illustrate how this result can be considered a coordination failure in the tradition of Cooper and John (1988).

[^2]
### 3.1 Groups face different market conditions

In this subsection we will consider a discriminatory equilibrium based on the one derived by L\&S. In the equilibrium the wage setting schedules of two types of people in the economy differs because of a difference in the reliability of the labor market signal the two groups send. We will assume that the economy consists of two groups of people characterized by an obvious characteristic. Clearly, gender and race are two of them, but we can also consider less obvious things like obesity, baldness, etc.. Both groups consist of a continuum of agents on $(0,1)$ and each one's type, $\theta_{i} \in\{\underline{\theta}, \bar{\theta}\}$, is common knowledge. In the simple equilibrium model developed in the previous section there is no interaction between the two groups. Hence, we can simply look at the two separate equilibrium $\beta$ 's, i.e. $\underline{\beta}$ and $\bar{\beta}$ for the groups of type $\underline{\theta}$ and $\bar{\theta}$ respectively. Following L\&S we will make the following assumption ${ }^{4}$.

Assumption 3.1: (Lundberg and Starz (1983)) Let $\underline{\sigma}_{a}^{2}, \bar{\sigma}_{a}^{2}, \underline{\sigma}_{b}^{2}$ and $\bar{\sigma}_{b}^{2}$ denote the variances of the learning ability levels and the initial human capital levels of the two groups and, correspondingly, let $\underline{\sigma}_{\varepsilon}^{2}$ and $\bar{\sigma}_{\varepsilon}^{2}$ be the variances of the noise in the labor market signals, then (i) $\underline{\sigma}_{a}^{2}=$ $\bar{\sigma}_{a}^{2}=0$, (ii) $\underline{\sigma}_{b}^{2}=\bar{\sigma}_{b}^{2}>0$, (iii) $\underline{\sigma}_{\varepsilon}^{2}>\bar{\sigma}_{\varepsilon}^{2}$.

This assumption has basically the following two implications. First, since (i) implies that everyone has the same marginal product of education, that is $a_{i}$ is equal for all agents, everyone will decide on identical educational levels. Second, (ii) and (iii) imply that the labor market signal of people with type $\underline{\theta}$ is less reliable than that of the ones with type $\bar{\theta}$, that is the signal to noise ratios satisfy $\frac{\sigma_{b}^{2}}{\underline{\sigma}_{\varepsilon}^{2}}<\frac{\bar{\sigma}_{b}^{2}}{\bar{\sigma}_{\varepsilon}^{2}}$.

Under this assumption the equilibrium condition (3) implies that

$$
\underline{\beta}=\frac{\underline{\sigma}_{b}^{2}}{\underline{\sigma}_{b}^{2}+\underline{\sigma}_{\varepsilon}^{2}}=\frac{1}{1+\frac{\sigma_{\varepsilon}^{2}}{\underline{\sigma}_{b}^{2}}}, \quad \text { and } \quad \bar{\beta}=\frac{1}{1+\frac{\bar{\sigma}_{\varepsilon}^{2}}{\bar{\sigma}_{b}^{2}}}
$$

It follows from assumption 3.1 that $\beta<\bar{\beta}$, because of the difference in the reliability of the labor market signals between the two groups. Hence, this

[^3]is clearly a discriminatory equilibrium because the difference in the market conditions faced by the groups with equal initial endowments of productive potential lead to an ex post difference in the wage setting schedule faced by the two groups. The problem with the discriminatory outcome of this equilibrium is that it is completely based on the assumption that the labor market signal of one group is less reliable than that of another which is hardly verifiable. Hence, while for this type of equilibrium one does not have to assume that groups differ in their productive potential, one still has to argue why groups differ in the reliability of their labor market signal ${ }^{5}$. Furthermore, this equilibrium, similar to that of Kremer (1993), is one in which everyone chooses identical educational levels. It would be more realistic to consider the case in which for each group we obtain a distribution of educational investments that is not degenerate. In the next subsection we will derive such an equilibrium and show that it is exactly the fluctuation in the variance of the human capital distribution, which we model introducing heterogeneity in the marginal ability to learn, what can generate the strategic complementarities necessary for the existence of multiple equilibria.

### 3.2 Groups face identical market conditions: Multiple equilibria

In this subsection we will consider parameter combinations of the model that yield the existence of multiple equilibria. All these equilibria have the property that, within each group, there is a distribution of education levels. This is caused by the fact that individuals each have a random marginal ability to learn, i.e. $\sigma_{a}^{2}>0$ for both groups. In the first part we will look at the case in which $\underline{\sigma}_{b}^{2}=\bar{\sigma}_{b}^{2}=0$ and will derive the exact parameter combinations that yield multiplicity. In the second part we will consider the general case in which $\underline{\sigma}_{b}^{2}$ and $\bar{\sigma}_{b}^{2}$ do not necessarily equal zero and present a similar analysis. Finally, we will briefly discuss the possible reasons why different groups might end up in different equilibria.

Before studying the general case, we will first consider the case in which $\underline{\sigma}_{b}^{2}=\bar{\sigma}_{b}^{2}=0$. That is, we will make the following assumption

[^4]Assumption 3.2 Let $\underline{\sigma}_{a}^{2}, \bar{\sigma}_{a}^{2}, \underline{\sigma}_{b}^{2}$ and $\bar{\sigma}_{b}^{2}$ denote the variances of the learning ability levels and the initial human capital levels of the two groups and, correspondingly, let $\underline{\sigma}_{\varepsilon}^{2}$ and $\bar{\sigma}_{\varepsilon}^{2}$ be the variances of the noise in the labor market signals, then (i) $\underline{\sigma}_{a}^{2}=\bar{\sigma}_{a}^{2}=\sigma_{a}^{2}>0$, (ii) $\underline{\sigma}_{b}^{2}=\bar{\sigma}_{b}^{2}=\sigma_{b}^{2}=0$, (iii) $\underline{\sigma}_{\varepsilon}^{2}=\bar{\sigma}_{\varepsilon}^{2}=\sigma_{\varepsilon}^{2}$.

This assumption is made for analytical convenience, because it leads to a simplification of (3) that turns out to be tractable. The main difference between this assumption and assumption 3.1 is that, since $\sigma_{a}^{2}>0$, the collective educational decisions are going to influence the variance of the human capital distribution and therefore the wage setting schedule. That is, if everyone in a group would decide to increase their educational level, this would lead to an increase in $\sigma_{h}^{2}$ and therefore to an increase in $\beta$. This increase in $\beta$ would in turn increase each individuals' incentive to invest in education. Hence, assuming $\sigma_{a}^{2}>0$ yields a strategic complementarity, as described by Cooper and John (1988) ${ }^{6}$.

In the following we will derive the conditions under which there is more than one equilibrium, that is the conditions under which ex post the groups might behave differently. This amounts to showing that the function $f$ : $[0,1] \rightarrow[0,1]$ defined by

$$
\begin{equation*}
f^{*}(\beta)=\frac{\beta^{\frac{2 \gamma}{1-\gamma}}}{\beta^{\frac{2 \gamma}{1-\gamma}}+\frac{\sigma_{\tilde{2}}^{2}}{\tilde{\sigma}_{a}^{2}}} \tag{4}
\end{equation*}
$$

can have more than one fixed point. This is formally stated in the following proposition which is proved in the appendix.

Proposition $1 \widehat{\beta}=0$ is always a fixed point of the function $f^{*}$ defined in equation (4). There might be one or two additional fixed points, depending on the following three cases:
(i) $\gamma<\frac{1}{3}: f^{*}$ has one $\widehat{\beta} \in(0,1)$.
(ii) $\gamma=\frac{1}{3}: f^{*}$ has one $\widehat{\beta} \in(0,1)$ if $\frac{\sigma_{c}^{2}}{\widehat{\sigma}_{a}^{2}}<1$.
(iii) $\gamma>\frac{1}{3}: f^{*}$ has either one, or two fixed points $\widehat{\beta} \in(0,1)$ if $\frac{\sigma_{\varepsilon}^{2}}{\widehat{\sigma}_{a}^{2}}$ is equal or lower, respectively, to $\left(\left(\frac{\eta}{1+\eta}\right)^{\eta}-\left(\frac{\eta}{1+\eta}\right)^{\eta+1}\right)$, where $\eta=\frac{3 \gamma-1}{1-\gamma}$.

[^5]Hence, for all values of $\gamma$ we obtain a degenerate equilibrium in which no one invests in education. Economically, this simply implies that if no one else is educated, employers do not expect an individual to be educated and thus do not reward this, making it optimal not to invest in education either. As we will show below this result changes in case $\sigma_{b}^{2}>0$.

Focusing on the equilibria where $\widehat{\beta} \in(0,1]$, we find that there can be more than one interior equilibria in case the degree of concavity of the schooling technology is low. Basically, we can distinguish two effects that reinforce each other. First, collectively increasing the level of education leads to a higher average productivity. Second, collectively increasing the level of education leads to a higher variance of human capital levels and thus to a higher equilibrium $\beta$. These two effects, which reinforce each other, lead to strategic complementarities and the possible existence of multiple equilibria. That is, if the second effect is strong enough multiple equilibria are possible. Since the increase in the variance is decreasing in the concavity of $S(e)$, we find that strategic complementarities are stronger the bigger $\gamma$.

A surprising result from the proof of proposition 1 is that the higher the ratio $\frac{\widetilde{\sigma}_{a}^{2}}{\sigma_{2}^{2}}$, the lower the interior equilibrium value of $\beta$ when multiplicity occurs. Of course, the distance between the two equilibrium $\beta$ is as well increasing in it. That means that the model can only generate reasonable equilibria for intermediate values of such ratio. When the signal is too noisy in relation to the variance of the learning ability multiple equilibria might not exist. In the opposite case, differences in the interior $\beta s$ would be too large. This is illustrated in figure 1, where we depict $f^{*}(\beta)$ for several parameter combinations. Finally, as demonstrated in the appendix, for multiplicity to exists in this case, we need $\sigma_{\varepsilon}^{2}<\tilde{\sigma}_{a}^{2}$, that is, the variation in productivity due to the component of the marginal ability to learn must be larger than the noise.

For the general case in which $\sigma_{b}^{2} \geq 0$ we get the following result:
Proposition 2 The fixed point properties of the function $f^{*}$, defined in equation (3), are determined according to two cases:
(i) $\gamma \leq \frac{1}{3}: f^{*}$ has one fixed point, $\widehat{\beta} \in(0,1)$.
(ii) $\gamma>\frac{1}{3}: f^{*}$ has either one, two or three fixed points, $\widehat{\beta}_{i} \in(0,1), \forall i$.

Figures 2 and 3 illustrate the effect of a change in $\sigma_{b}^{2}$ and $\gamma$ respectively ${ }^{7}$. Because the larger $\sigma_{b}^{2}$, the smaller the influence of the educational choice on

[^6]the equilibrium outcome, when $\sigma_{b}^{2}$ is big enough relative to $\widetilde{\sigma}_{a}^{2}$ the multiple equilibria will be eliminated. This can be seen from figure 2 where it is clear that for large $\sigma_{b}^{2}$ the low (interior) equilibrium is eliminated. From figure 3 it can be seen that the less concave the schooling technology the less decreasing the returns to education and the more people invest in human capital. Hence, the high equilibrium is increasing in $\gamma$.

Although the model introduced explains the possibility of two identical groups ending up in different equilibria it does not address the question why this would actually be the case. Two explanations, both initially considered by Arrow (1972), have mostly been analyzed in the literature. Both theories are based on assumptions about beliefs that are not explicitly modeled. The first explanation, known as that of negative stereotypes, assumes that employers have a negative prejudism against employees from a certain group. Such an expectation might actually lead to a decreased incentive for individuals from this group to invest in human capital. This decreased in investment would lead this group to become less productive and thus to these negative stereotypes being self fulfilling. The second explanation is an attempt to explain the evolution of discrimination over time. It assumes that employers have adaptive expectations about the human capital distributions of the groups, i.e. they base their expectations on the situation in the previous period. Such an assumption would lead to the following law of motion for $\beta$

$$
\begin{equation*}
\beta_{t+1}=f\left(\beta_{t}\right) \tag{5}
\end{equation*}
$$

which yields the phase diagram depicted in figure 4 , where $A$ and $C$ are stable equilibria and $B$ is unstable. Equation (5) implies that whether a group moves to equilibrium $A$ or $C$ fully depends on their initial $\beta$. Hence, assuming that one group starts below $A$ and the other one in between $B$ and $C$, would allow for a situation in which the "discriminated" group initially seems to catch up with the other one, but eventually this catch up effect stagnates and ultimately there would be a persistent gap between the group that is determined by the difference between $A$ and $C$.

A third explanation that has not yet been considered in the economic literature on discrimination, but that seems to be supported by some empirical findings from psychology, is the possibility of a negative self image of certain
$\overline{\sigma_{e}^{2}=1}$ and $\gamma=0.5$, while $\mu_{a}=\gamma^{\gamma}-\frac{1}{2} \sigma_{a}^{2}$. This parameter combination is chose because it captures L\&S degree of concavity and yields multiple equilibria as shown in proposition 2.
groups. This again explains discrimination as a self fulfilling prophecy but in this case there are not the employers but the people in the discriminated group themselves that have self fulfilling expectations. Suppose, that everyone in a group expects to be discriminated, then this might actually lead to a coordination failure that drives the group into the low wage - low productivity equilibrium. That negative self images are not purely hypothetical is shown, for example, by Steele (1997) who finds that when blacks, taking a test, were told that such tests showed no distinction in white-black scores, they do as well as white test-takers. But when they are told nothing, or have to tell their race, their scores are lower than those of whites. An obvious possible reason why groups might have a negative self image is because of past experience. In the most extreme case this would mean that even though policies might successfully have eliminated previously existing discriminatory market conditions, the fact that people don't believe in these policies might still lead to ex ante identical groups in society, ex post, to obtain different average productivity levels and wages.

### 3.3 Policy implications

It turns out that the two scenarios usually considered in the economic literature presented above have very different implications for possible affirmative action and anti-discrimination policies. The main point is that policies can more easily be used to change incentives than to change expectations. That is, if groups face different market conditions, it is often possible to overcome these differences by using policies to change incentives. In particular, L\&S show that in the situation described in 3.1, imposing the same wage setting schedule for both groups leads to a Pareto dominant outcome. As Lundberg (1991) shows, this result is not robust against the assumption that the true wage schedule is not perfectly observed by the authorities, but has to be estimated. More importantly, consider imposing the same wage setting schedule in case of a coordination failure. In that case, there are two possibilities: Both groups obtaining the high-productivity/high-wage equilibrium versus both groups obtaining the low equilibrium. The former would clearly be a preferred situation, but we have no argument why the economy would end up in that situation.

In a model in which workers are either hired (or promoted) for skilled jobs or not, Coate and Loury (1993) show that there is another important drawback to imposing equal standards, in this case considered hiring/promotion
rates, for two groups in case they differ because of a coordination failure. Such a policy would give employers the incentive to put up lower standards for one group than for the other and therefore lowering the low-productivity group's incentive to increase its productivity, leading to an even more severe productivity disparity between both groups. This is known as a "patronizing" equilibrium. Benoit (1994) criticizes this conclusion. He shows that Coate and Loury's patronizing equilibria can be avoided by imposing a policy that enforces a gradual adjustment to equal hiring/promotion rates.

Throughout the discussion on the effectiveness of affirmative action policies in eliminating discriminatory labor market situations, one has to bear in mind that, though the scenarios presented in sections 3.1 and 3.2 and also scenarios about differences in school quality between various groups seem to be competitive, the discrimination we observe in reality is probably a combination of all of them. This would imply that we probably need more than one drug to cure the disease. In order to assess which policy might be most effective it is important, though, to determine which scenario is the most relevant in practice. For this reason, we introduce an econometric exercise in the next section.

## 4 Empirical Model

As shown in Sections 2 and 3, the two types of discriminatory equilibria considered have very different causes of discrimination and therefore also very different policy implications. It is therefore important to consider whether it is actually possible to empirically distinguish the two cases. In this section we will use a simple econometric analysis to test the main implication of the coordination failure equilibria: Groups with identical human capital distributions would face identical wage setting schedules. Hence, contrary to previous empirical studies of discrimination, like for example Trejo (1997) and O'Neill (1992), we will not only relate an individual's wage to their own human capital level but also to the distribution of human capital in the group they belong to.

Contrary to the coordination failure theory of discrimination, all other theories assume that groups face different market conditions that cause these groups to end up in different equilibrium outcomes. This would imply that, even when groups have the same human capital distribution, these different market forces would always cause these groups to end up in a discriminatory
situation. The coordination failure theory, however, suggests that, because groups are identical and face similar market conditions, if they would have the same human capital distribution then they would end up in the same equilibrium and face identical wage setting schedules. This suggests a testable null hypothesis. We could test for the existence of a coordination failure by testing whether if two groups would have same human capital distribution they would face same wage setting schedule. We can think of this as assuming that the standard $\log$ wage regression, $w_{i}^{j}=\alpha \cdot X_{i}^{j}$, used by employers to compensate worker $i$ of group $j$ for his productivity, would be a function not only of his individual characteristics, but also of the human capital distribution of the group to which the he belongs, $w(h, f(h))$, to rewrite it as $w_{i}^{j}=\alpha\left(Z^{j}\right) \cdot X_{i}^{j}$, where $Z^{j}$ is a vector of characteristics of the group to which the worker belongs. The later is what we refer to as the augmented model while we refer to the former as the standard model. If we calculate differences in the wage schedules according to the standard model, and then we repeat the exercise with the augmented model, we would expect to extract the differences in the coefficients with those of the human capital distributions, which in short implies that differences in wage schedules found with the augmented model should be lower.

Our empirical analysis consists of five parts. In the first part we describe the data, taken from the Current Population Survey, that we use for our analysis. We then proceed, in the second subsection, by estimating a separate log wage equation for both black and white males for each year in our sample, i.e. 1964-1998. Following Trejo (1997), we use these estimates to assess which part of the log wage differences is caused by the differences in the coefficients in the wage equations. Similar to Trejo, we find that at the beginning of the period, about $75 \%$ of the difference in average $\log$ wages are caused by the differences in the coefficients instead of the differences in human capital levels, while at the end, notably during the 90s, it accounted for less than $50 \%$ of it. In the third subsection, we introduce an augmented wage regression which, following the theory of statistical discrimination, tries to explain the differences in the coefficients of the wage schedule from the differences in the human capital distributions of the two groups. The results that we obtain with this augmented wage regression seem to be at odds with the coordination failure theory of discrimination. In the following section we turn to a maximum likelihood estimation in other to account for potential biases with the OLS estimations. Finally, we discuss the limitations of our methodology and possible extensions.

### 4.1 Data

For our analysis we have used data from the Census Bureau's Current Population Surveys uniform March files for the years 1964-1998 ${ }^{8}$. The data cover information on yearly salaries and wages, potential experience and education for black and white males aged 25-68.

We use the log of hourly earnings in our estimations ${ }^{9}$ Unfortunately, the data on salaries and wages are topcoded at $\$ 50000$ and thus we have to limit our analysis to men with wages and salaries smaller than this ceiling level for the OLS estimations. We do it though, after converting the dollars of each year to dollars of 1981 in order to get comparable samples from year to year. As it has become standard, we construct potential experience as age minus the number of years of education completed minus six, while education is simply the number of years of education completed. We consider the sample of men. Table 1 presents descriptive statistics for the variables considered for both groups during the period analyzed.

### 4.2 Standard log wage regression

For our standard log wage regressions we will follow Trejo (1997) and explain a person's wages and salaries as a function of his experience and education ${ }^{10}$. In particular, we will consider a regression of the form

$$
\begin{equation*}
\ln w_{i g t}=\beta_{0 g t}+\sum_{j=1}^{5} \beta_{j g t} x_{i j g t}+\sum_{j=6}^{10} \beta_{j g t} d_{i j g t}+u_{i g t} \tag{6}
\end{equation*}
$$

where $w_{i g t}$ denotes yearly wages and salaries (reported) in period $t$ of person $i$ from group $g$, where $g \in\{$ black, white $\}$. In particular, $x_{i 1 g t}$ is a dummy

[^7]variable for individuals with incomplete high school, i.e., with less than 12 years of education, $x_{i 2 g t}$ is a dummy variable for individuals with incomplete college, i.e., with more than 12 and less than 16 years of education, $x_{i 3 g t}$ is a dummy variable for individuals with college or more, i.e., with more than 16 years of education, $x_{i 4 g t}$ is potential experience and $x_{i 5 g t}$ is potential experience squared. Finally, $d_{i j g t}$ are the dummy variables included.

The results of these regressions for the years 1964-1998 for both, black and white males, are reported in table 2. From this table it can be seen that the estimated coefficients vary both over time and between blacks and whites. In order to assess the extent of discrimination in our sample we consider the following decomposition of the differences in average log wages between the white and black males in our sample.

$$
\begin{aligned}
\overline{\left(\ln w_{w t}\right)}-\overline{\left(\ln w_{b t}\right)}= & {\left[\left(\beta_{0 w t}-\beta_{0 b t}\right)+\sum_{j=1}^{5}\left(\beta_{j w t}-\beta_{j b t}\right) \bar{x}_{j b t}+\sum_{j=6}^{10}\left(\beta_{j w t}-\beta_{j b t}\right) \bar{d}_{j b t}\right] } \\
& +\left[\sum_{j=1}^{5} \beta_{j w t}\left(\bar{x}_{j w t}-\bar{x}_{j b t}\right)+\sum_{j=6}^{10} \beta_{j w t}\left(\bar{d}_{j w t}-\bar{d}_{j b t}\right)\right]
\end{aligned}
$$

where the first term in brackets on the right hand side denotes the part of the difference in the average log wages that is caused by differences in the coefficients of the estimated wage equations and the second term is the part caused by the differences in human capital levels. Trejo (1997) reports for 1979 and 1989 that for Mexican American most of the average wage differentials can be explained by the second term, i.e. differences in human capital levels. According to our results, as we mentioned, when comparing whites with black males the first part seems to explain about $75 \%$ of the differential at the beginning of the period and less than $50 \%$ at the end as it is illustrated in figure 6. It is remarkable the reduction in the relative importance of the differences caused by the coefficients in explaining log wage differences. They are though, statistically significant from zero all the years. Since our estimation does not consider factors difficult to account for as family environment, neighborhoods, unobserved ability and others, the results found in our estimation suggest that the contribution to the log wage differential due to the wage schedules might be substantially overestimated ${ }^{11}$.

[^8]This result is in accordance with previous literature which consider that labor market discrimination is not any more the major source of the disparity in earnings between blacks and whites, as pointed out by Heckman (1998). We consider though, that the mentioned reduction in importance should not lead to a relaxation of civil rights laws, which have proven effective after the passage of the 1964 Civil Rights Act, as shown in our results, where can be appreciated how the large part of the reduction in the wage differential took place roughly during the first decade analyzed, i.e. from 1964 until 1965, period which followed the passage of the mentioned Act. This point have been previously made by Donohue and Heckman (1991).

### 4.3 Augmented log wage regression

From the standard wage regressions we obtained that the coefficients in the estimated wage setting schedule for black males are very different from those of white males. It is thus important to consider a theory that explains why these differences occur. In this section we introduce the augmented model, by which the productivity of individual $i$ which belongs to group $j$ is assessed according to $w_{i}^{j}=\alpha\left(Z^{j}\right) \cdot X_{i}^{j}$, where $Z^{j}$ is a vector of characteristics of the group to which the worker belongs. We expect to extract the differences in the coefficients with those of the human capital distributions, which in short implies that differences in wage schedules found with the augmented model should be lower.

The purpose of the augmented wage regression presented here is to try to explain the differences in the estimated coefficients presented in table 2 from differences in the shape and evolution of the human capital distributions of the black and white males in our sample. This, off course, means that we implicitly assume that employers base their expectations on a person belonging to the population of men from which we have selected our sample. A more advanced empirical analysis would preferably consider the joint human capital distribution for all black and white males. Our approach though, follows the assumptions of our theoretical model which does not rely on any kind of complementarities between the groups.

Similar to the previous subsection we consider potential experience and education as the main indicators of human capital and will thus consider

[^9]the distribution of human capital levels as the joint distribution of these two variables. Figures 7 to 10 depict the evolution of the marginal distributions of both education and experience for the black and white males in our sample. It is clear that during the analyzed period blacks caught up significantly in both characteristics, so that their distributions are converging. Let $e_{i g t}$ denote education and $x_{i g t}$ experience of person $i$ in group $g$ in period $t$. Then we will consider the following sample moments of the joint distribution of $e$ and $x$.
\[

$$
\begin{aligned}
\mu_{g t}^{10} & =\frac{1}{n_{g t}} \sum_{i=1}^{n_{g t}} x_{i g t} \\
\mu_{g t}^{01} & =\frac{1}{n_{g t}} \sum_{i=1}^{n_{g t}} e_{i g t}
\end{aligned}
$$
\]

and

$$
\mu_{g t}^{r s}=\frac{1}{n_{g t}} \sum_{i=1}^{n_{g t}}\left(x_{i g t}-\mu_{g t}^{10}\right)^{r}\left(e_{i g t}-\mu_{g t}^{01}\right)^{s}
$$

where $n_{g t}$ is the number of individuals in our sample for group $g$ in period $t$. Clearly the sample moments $\mu_{g t}^{r s}$ are consistent estimates of population moments $m_{g t}^{r s}$, as long as they exist.

We will now present the augmented wage regression assuming that the coefficients $\beta$ depend linearly on the (cross)-moments of the first, second and third order of the joint distribution of education and experience ${ }^{12}$, i.e.

$$
\beta_{p g t}=z_{p g}^{(0.0)}+\sum_{i=1}^{3} \sum_{j=0}^{i} z_{p g}^{(j . i-j)} m_{g t}^{j, i-j}
$$

Since we have to approximate the population moments $m_{g t}^{r s}$ with their sample counterparts $\mu_{g t}^{r s}$, we will assume in our application that for $p=0, \ldots, k$.

$$
\beta_{p g t}=z_{p g}^{(0.0)}+\sum_{i=1}^{3} \sum_{j=0}^{i} z_{p g}^{(j . i-j)} \mu_{g t}^{j, i-j}+\varepsilon_{p g t} \quad \text { with } E\left[\varepsilon_{p g t}\right]=0
$$

Substituting this in the standard wage equation (6) we obtain the following reduced form regression equation

$$
\ln w_{i g t}=\left\{z_{0 g}^{(0.0)}+\sum_{i=1}^{3} \sum_{j=0}^{i} z_{0 g}^{(j . i-j)} \mu_{g t}^{j, i-j}\right\}
$$

[^10]\[

$$
\begin{aligned}
& +\sum_{p=1}^{k}\left\{z_{p g}^{(0.0)}+\sum_{i=1}^{3} \sum_{j=0}^{i} z_{p g}^{(j . i-j)} \mu_{g t}^{j, i-j}\right\} x_{i p g t} \\
& +\left\{\varepsilon_{0 g t}+\sum_{p=1}^{k} \varepsilon_{p g t} x_{i p g t}+u_{i g t}\right\}
\end{aligned}
$$
\]

using the following matrix notation

$$
\begin{aligned}
z_{g} & =\left[z_{0 g}^{(0,0)}, \ldots, z_{0 g}^{(0,3)}, \ldots, z_{k g}^{(0,0)}, \ldots, z_{k g}^{(0,3)}\right]^{\prime} \\
\mu_{g t} & =\left[1, \mu_{g t}^{(2,0)}, \mu_{g t}^{(0,1)}, \ldots, \mu_{g t}^{(0,3)}\right]^{\prime} \\
x_{i g t} & =\left[1, x_{i 1 g t}, \ldots, x_{i k g t}\right]^{\prime} \\
v_{i g t} & =\left\{\varepsilon_{0 g t}+\sum_{p=1}^{k} \varepsilon_{p g t} x_{i p g t}+u_{i g t}\right\} \\
\omega_{i g t} & =x_{i g t} \otimes \mu_{g t}
\end{aligned}
$$

we can rewrite this equation as

$$
\begin{equation*}
\ln w_{i g t}=\omega_{i g t}^{\prime} z_{g}+v_{i g t} \tag{7}
\end{equation*}
$$

Two things are key when considering the estimation of (7). First, in order for the estimates of the parameter vector $z_{g}$ to be consistent, it must hold that $E\left[\omega_{i g t} v_{i g t}\right]=0$. A sufficient condition would be that $\varepsilon_{p g t}$ and $u_{i g t}$ are independent of the explanatory variables, $x_{i g t}$, and the sample moments, $\mu_{g t}$. Additionally to the well known criticism to the standard log wage regression that $u_{i g t}$ might be positively correlated with unobserved skills that also positively affect a persons education level, $x_{i 3 g t}$, the above assumptions also imply that the measurement errors $\varepsilon_{p g t}$ in the sample moments are also independent of the observations on the basis of which they are estimated. Although in the following we will make the assumptions described above and will use ordinary least squares to estimate (7), we are well aware that an instrumental variable estimation might be considered more appropriate.

The second econometric issue to consider in estimating (7) is that we consider a sequence of cross-sections, i.e. $i=1, \ldots, n_{g t}$ and $t=1, \ldots, T$, and that, contrary to standard cross section techniques, our parameter estimates are only consistent whenever both $n_{g t}$ and $t$ go to infinity. This is the case because we need to observe both an infinite number of individuals to estimate the sample moments $\mu_{g t}^{r s}$ consistently and observe the wage setting schedule
for an infinite number of different human capital distributions in order to estimate the dependence of the wage setting schedule on the distribution consistently.

In our application we have used real salaries and wages in 1981 dollars as dependent variables and added a deterministic trend as a proxy for technological change causing real wage increases over time.

Table 4 contains the estimation result for equation (7) for both black and white males for the period 1964-1998 using only the second moments of education and experience, avoiding this way the problems caused by multicollinearity perceived in table 3 . The coordination failure theory of discrimination would suggest that $z_{b}=z_{w}$, which, as can be easily seen from table 4 , is clearly not the case. Just as for the standard log wage regression we use (7) to decompose the average log wage differences into a part explained by parameter differences and a part explained by differences in average human capital levels (and average residuals), i.e.

$$
\begin{equation*}
\overline{\left(\ln w_{w t}\right)}-\overline{\left(\ln w_{b t}\right)}=\bar{\omega}_{w t}^{\prime}\left(z_{w}-z_{b}\right)+\left(\bar{\omega}_{w t}^{\prime}-\bar{\omega}_{b t}^{\prime}\right) z_{b}+\left(\bar{v}_{w t}-\bar{v}_{b t}\right) \tag{8}
\end{equation*}
$$

Hence, since the coordination failure theory of discrimination predicts that $z_{b}=z_{w}$, it would imply that the part of the average log wage differences caused by differences in the coefficients, i.e. $\bar{\omega}_{w t}^{\prime}\left(z_{w}-z_{b}\right)$, is zero. However, as can be seen from figure 12 , for almost every period $\bar{\omega}_{w t}^{\prime}\left(z_{w}-z_{b}\right)$ seems to exceed the part caused by coefficient differences found on the basis of the standard $\log$ wage regression in figure 11. Thus, our results seem to suggest that, after correcting for possible statistical discrimination, discrimination due to other causes seems to be more severe than when not correcting for it. This is completely the opposite result from what is predicted by the theory of discrimination as a coordination failure which would suggest that the only cause of discrimination is statistical.

However, one has to be careful interpreting the above results. There are several grounds that might lead to possible biases in the analysis presented above. They can be basically put in three categories: (i) sample selection bias and truncation due to topcoding of earnings, (ii) model specification, and (iii) estimation issues.

Sample selection bias almost certainly occurs in our sample, because we have only selected employees with total earnings below $\$ 50,000$. If one would believe in a theory of statistical discrimination then one of the questions is with which group are (potential) employees identified. Suppose that our
simple specification in (7) was actually correct but that the males in our sample were not only judged on their human capital distribution but on that of all males of their ethnic group. In that case, our sample selection, implies that we ignore the fact that the black males in our sample are actually associated with a group of men that has a high unemployment rate and lower human capital levels than represented by the human capital distribution used in our empirical analysis.

The specification of (7) is ad hoc and not directly based on any microeconomic foundations. In particular, it is hard to believe that the resulting wage equation coefficients are a simple linear function of the moments of the underlying human capital distribution. Furthermore, the proxies that we have used for human capital levels, i.e. education and potential experience, might not accurately reflect the characteristics on the basis of which employers form their expectations. Anyway, what our analysis suggests is that any empirical analysis that considers the possibility of statistical discrimination should include the possibility of the coefficients in the wage equation depending on group wide characteristics.

Finally, there are some practical econometric issues that complicate the estimation of (7). First, there is the possible correlation of the residuals with the explanatory variables that might cause inconsistency of our estimates, as discussed above. Secondly, even if a linear specification as the one we use is correct, there still remains the question of how accurately the sample moments we selected capture the distribution of human capital in each group.

### 4.4 Maximum Likelihood Estimation

In this section we present a model that correct both the selectivity problems due to the participation decision in the labor market and the truncation in the standard log wage regression. Consistent results with those obtained by OLS would, arguably, suffice to consider the results of the previous models reliable.

## The Model

We use a model with two equations with latent variables which incorporates elements of the models found in Heckman (1974) and Hausman and Wise (1977):

$$
h^{*}=\alpha_{0}+\alpha_{1} \cdot w+Z \cdot \alpha+e_{h}
$$

$$
\begin{gathered}
w^{*}=\beta_{0}+X \cdot \beta+e_{w} \\
\left.\begin{array}{l}
y=w^{*}+h^{*} \\
w=w^{*} \\
h=h^{*} \\
y=L \\
h=h^{*}
\end{array}\right\} \quad \begin{array}{l}
\text { if } h^{*}>0, w^{*}+h^{*}<L \\
y=w=h=0\} \\
\text { if } h^{*}>0, w^{*}+h^{*} \geq L \\
\text { if } h^{*} \leq 0
\end{array} \\
\begin{array}{l}
\left(e_{h}, e_{w}\right)^{\sim} N\left(0,0, \sigma_{h}, \sigma_{w}, \rho\right)
\end{array}
\end{gathered}
$$

where $h$ is the log of the number of hours worked last year, $y$ is the log of total earnings per year and $w$ is the log of total earnings per hour. $Z$ includes variables like other income, spouse's income and number of persons in household under age 18. Variables in $X$ are the same as those included in the standard log wage regression.

The reduced form of the hours equation is

$$
h^{*}=R \cdot \gamma+v
$$

where $R=\left[\begin{array}{lll}1 & X & Z\end{array}\right], \gamma=\left[\begin{array}{lll}\alpha_{0}+\alpha_{1} \beta_{0} & \alpha_{1} \beta^{\prime} & \alpha^{\prime}\end{array}\right]^{\prime}$, and $v=$ $\alpha_{1} e_{w}+e_{h}$.

We estimate the model for each group by Full Information Maximum Likelihood. The likelihood function to estimate is:

$$
L=\prod_{\Psi_{0}^{j}}\left[1-\Phi\left(\frac{R \cdot \gamma}{\sigma_{v}}\right)\right] \cdot \prod_{\Psi_{1}^{j}} f(h, w) \cdot \prod_{\Psi_{2}^{j}} \int_{L}^{\infty} f\left(h, y^{*}\right) d y^{*}
$$

$j=B, W$. The sets $\Psi_{i}^{j}, i=0,1,2$, represent the sets of people who do not work $(i=0)$, work and have $y<L(i=1)$, and work and have $y \geq L$ $(i=2) . \Phi$ and $\phi$ are the distribution and density functions of the normal distribution, $f(h, w)$ is the bivariate normal distribution of $h$ and $w, f(h, y)$ is the bivariate normal distribution of $h$ and $y$, and $f\left(y^{*} \mid h\right)$ is the density of $y^{*}$ conditional on $h$.

The source of bias can be appreciated from the fact that we only observe $w$ and $h$ conditional on their being positive in the case of the hours of work, and when $h$ is positive and $y$ is less than $L$ in the case of $w$.

Below we describe the different components of the log wage difference in this case, and point at those which we will focus on.

## Wage Decomposition

In this case, the observed wage gap between blacks and whites, defined by

$$
E\left[w_{B} \mid \Omega_{1}^{B}\right]-E\left[w_{W} \mid \Omega_{1}^{W}\right] \equiv \bar{w}_{B}-\bar{w}_{W}
$$

is determined by
$\bar{w}_{B}-\bar{w}_{W}=\left(\beta_{B 0}-\beta_{W 0}\right)+\bar{X}_{W}\left(\beta_{B}-\beta_{W}\right)+\left(\bar{X}_{B}-\bar{X}_{W}\right) \beta_{B}+E\left[u_{B} \mid \Omega_{1}^{B}\right]-E\left[u_{W} \mid \Omega_{1}^{W}\right]$
where $\bar{X}_{j} \equiv E\left[X_{j} \mid \Omega_{1}^{j}\right]$.
The difference due to the different wage schedules of the two groups is

$$
\left(\beta_{B 0}-\beta_{W 0}\right)+\bar{X}_{W}\left(\beta_{B}-\beta_{W}\right)
$$

The difference due to the different wage-related characteristics of the two groups is

$$
\left(\bar{X}_{B}-\bar{X}_{W}\right) \beta_{B}
$$

And finally, the remaining term, $\left[E\left(u_{B} \mid \Omega_{B}\right)-E\left(u_{W} \mid \Omega_{W}\right)\right]$ is due to selectivity. This decomposition, which differs to the previously presented only by the term involving selection, was also used previously by Schafgans (1998) to evaluate ethnic wage differences. Here, we will fucus only in the component due to the coefficients in order to compare it with our result with the OLS estimation.

The results of the estimation are presented in table 5 and the decomposition of the log wage differential in figure 13. Figure 14 contrasts the two decompositions. With the exception of some years, the share of the log wage differential explained by the coefficients is very close in both cases. Years where substantial differences emerge are more likely due to problems in the estimation for the quality of the additional data used in the FIML estimation, which we expect to fix in the near future.

Since these results support those obtained in the standard model using OLS, estimates of the augmented model are very likely to be supported as well by a FIML estimation, for which we consider that the problem of selection does not affect our previous conclusions.

There still remain the limitations due to our model specification, and the previously mentioned econometric issues as possible ways to improve the model and get additional evidence of whether the theory of discrimination as a coordination failure, is ad odds with evidence, as we conclude with our empirical model.

## 5 Conclusion

In this paper we have shown, using a simple model of statistical discrimination, that groups with equal productive endowments might end up in equilibria in which they get different average wages. This might be possible because of the existence of multiple equilibria. These equilibria exist, because, in a world of imperfect information, an individual is not only judged on his own merits but also on those of the group he belongs to. If an individuals incentives to invest in his own productivity is increasing in the groups average investment level, then this mechanism causes a strategic complementarity that might be strong enough to accommodate multiple equilibria.

However, a simple econometric analysis suggests that average wage differentials between black and white men are not solely caused by the coordination failure theory of discrimination, which relies on the possibility of multiple equilibria in a model with ex-ante identical agents. The results showed that wage differentials would be larger, once we accounted for statistical discrimination. Before taking the empirical results in this paper for granted, and designating them as "stylized facts", a careful analysis of the effects of model specification and possibly worthwhile, some econometric refinements, might be necessary to verify our results.

On a theoretical level, it would be worthwhile to consider a model of statistical discrimination in which there is also strategic interaction between various groups in the economy, as for example done by Frijters (1997), Moro and Norman (1996) and Moro (1998), rather than considering the case in which each group behaves completely independently of the other.

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## A Proofs of propositions

Proof of proposition 1: From (4) it is immediately clear that $\widehat{\beta}=0$ is a fixed point, no matter which parameter values are considered.

If (4) has a fixed point $\widehat{\beta} \in(0,1]$, then this $\widehat{\beta}$ must satisfy

$$
\begin{equation*}
1=\frac{\widehat{\beta}^{\frac{3 \gamma-1}{1-\gamma}}}{\widehat{\beta}^{\frac{2 \gamma}{1-\gamma}}+\frac{\sigma_{\tilde{c}}^{2}}{\widehat{\sigma}_{a}^{2}}} \tag{9}
\end{equation*}
$$

Defining the function $g:(0,1] \rightarrow \Re_{+}$such that $g(\beta) \equiv \beta^{\eta}-\beta^{\eta+1}$ and $\eta=\frac{3 \gamma-1}{1-\gamma}$, this implies that $\widehat{\beta} \in(0,1]$ must solve

$$
\begin{equation*}
g(\widehat{\beta})=\frac{\sigma_{\varepsilon}^{2}}{\widehat{\sigma}_{a}^{2}} \tag{10}
\end{equation*}
$$

Since $\gamma \in(0,1)$ we find that $\eta \in(-1, \infty)$. Furthermore it can be easily seen that for all values of $\eta$ the function $g($.$) is continuous and differentiable with$ derivative $g^{\prime}(\beta)=\eta \beta^{\eta-1}-(\eta+1) \beta^{\eta}$ and $g(1)=0$. We can now distinguish three cases (i) $\gamma \in\left(0, \frac{1}{3}\right)$ which implies $\eta \in(-1,0)$, (ii) $\gamma=\frac{1}{3}$ which implies $\eta=0$, and (iii) $\gamma \in\left(\frac{1}{3}, 1\right)$ which implies $\eta \in(0, \infty)$. In case (i) we find that $\lim _{\beta \downarrow 0} g(\beta)=\infty$ and $g^{\prime}<0$, which implies that there is a unique $\widehat{\beta} \in(0,1]$ that solves (10). In case (ii) $g(\beta)=1-\beta$ and (10) has a solution as long as $\frac{\sigma_{\tilde{c}}^{2}}{\tilde{\sigma}_{a}^{2}}<1$. Finally, in case (iii) we know that $g(0)=g(1)=0$ and that the unique stationary point at which $g^{\prime}(\beta)=0$ equals $\widetilde{\beta}=\frac{\eta}{1+\eta}$ such that $g(\widetilde{\beta})=\left(\left(\frac{\eta}{1+\eta}\right)^{\eta}-\left(\frac{\eta}{1+\eta}\right)^{\eta+1}\right) \equiv A$, such that if $\frac{\sigma_{\varepsilon}^{2}}{\widetilde{\sigma}_{a}^{2}}=A$ then $\widetilde{\beta}$ is the unique solution to (10) and if $\frac{\sigma_{\sigma}^{2}}{\tilde{\sigma}_{a}^{2}}<A$ then (10) has two solutions. This is depicted in figure 5 . Notice that $1>A>0$, which implies that for multiple equilibria we need $\sigma_{\varepsilon}^{2}<\tilde{\sigma}_{a}^{2}$.

Proof of proposition 2: If (3) has a fixed point $\widehat{\beta} \in(0,1)$, then this $\widehat{\beta}$ must satisfy

$$
\begin{equation*}
\widehat{\beta}=\frac{(1-\widehat{\beta})}{\frac{\sigma_{\stackrel{e}{2}}^{\sigma_{a}^{2}}}{\sigma^{2}}}\left(\widehat{\beta}^{\eta+1}+\frac{\sigma_{b}^{2}}{\sigma_{a}^{2}}\right) \equiv G(\widehat{\beta}) \tag{11}
\end{equation*}
$$

Then, $G(\widehat{\beta}):(0,1) \rightarrow \Re_{+}$. Also in this case, it can be easily seen that for all values of $\eta$ the function $G($.$) is continuous and differentiable with first deriv-$ ative $G^{\prime}(\beta)=\frac{\beta^{\eta} \sigma_{\alpha}^{2}}{\sigma_{\varepsilon}^{2}}[(\eta+1)-\beta(\eta+2)]-\frac{\sigma_{b}^{2}}{\sigma_{\varepsilon}^{2}}$ and second derivative $G^{\prime \prime}(\beta)=$
$\frac{\beta^{\eta-1} \sigma_{\alpha}^{2}}{\sigma_{\varepsilon}^{2}}[\eta(\eta+1)-\beta(\eta+1)(\eta+2)]$. Notice that $G(0)=\frac{\sigma_{b}^{2}}{\sigma_{\varepsilon}^{2}}, G(1)=0$. We can now distinguish two cases (i) $\gamma \in\left(0, \frac{1}{3}\right]$ which implies $\eta \in(-1,0]$, and (iii) $\gamma \in\left(\frac{1}{3}, 1\right)$ which implies $\eta \in(0, \infty)$. In case (i) we find that $G^{\prime \prime}<0, \forall \beta$, which implies that there is a unique $\widehat{\beta} \in(0,1)$ that solves (11). In case (ii) $G$ is decreasing for $\beta$ close to either 0 or 1 and since $G^{\prime \prime} \geq 0$ for $\beta^{i} \leq \frac{\eta}{\eta+2}$, in this case, there is always an inflection point at $\beta^{i}=\frac{\eta}{\eta+2}$, so that the function is always initially decreasing and concave upwards and for values of $\beta$ larger than $\beta^{i}$ concave downwards as depicted in figure 5.A. Given this shape, depending upon de magnitude of the concavity, the function will intersect the diagonal either one, two or three times. Assume there exist $\beta_{1}$ and $\beta_{2}$ such that $\beta_{1}<\frac{\eta}{\eta+2}<\beta_{2}, G^{\prime}\left(\beta_{1}\right)=1$, and $G^{\prime}\left(\beta_{2}\right)=1$. The function will intersect the diagonal three times whenever $G\left(\beta_{1}\right)<\beta_{1}$, and $G\left(\beta_{2}\right)>\beta_{2}$. If $G\left(\beta_{2}\right)=\beta_{2}$ or $G\left(\beta_{1}\right)=\beta_{1}$ it will intersect it twice, otherwise, it will intersect it only once. That there exists such a combination of parameters is illustrated in figure 5.A where the function has three equilibria, and we selected $\widetilde{\sigma}_{a}^{2}=20, \sigma_{\varepsilon}^{2}=4, \sigma_{b}^{2}=0.15$, and $\gamma=1 / 2$.

Table 1. Descriptive statistics of variables
Black Males

| Year | 64 | 65 | 66 | 67 | 68 | 69 | 70 | 71 | 72 | 73 | 74 | 75 | 76 | 77 | 78 | 79 | 80 | 81 |
| :--- | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: |
| IHS | 0.71 | 0.69 | 0.69 | 0.66 | 0.66 | 0.63 | 0.62 | 0.62 | 0.59 | 0.56 | 0.53 | 0.49 | 0.49 | 0.46 | 0.43 | 0.41 | 0.37 | 0.37 |
|  | 0.45 | 0.46 | 0.46 | 0.47 | 0.47 | 0.48 | 0.48 | 0.49 | 0.49 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.49 | 0.48 | 0.48 |
| IC | 0.05 | 0.06 | 0.06 | 0.06 | 0.06 | 0.07 | 0.07 | 0.07 | 0.08 | 0.07 | 0.10 | 0.11 | 0.11 | 0.13 | 0.15 | 0.14 | 0.16 | 0.16 |
|  | 0.23 | 0.24 | 0.23 | 0.23 | 0.25 | 0.26 | 0.26 | 0.25 | 0.26 | 0.26 | 0.29 | 0.32 | 0.32 | 0.33 | 0.36 | 0.35 | 0.36 | 0.37 |
| C+ | 0.06 | 0.07 | 0.05 | 0.05 | 0.04 | 0.05 | 0.06 | 0.06 | 0.07 | 0.07 | 0.07 | 0.08 | 0.09 | 0.10 | 0.09 | 0.11 | 0.11 | 0.11 |
|  | 0.24 | 0.25 | 0.22 | 0.21 | 0.21 | 0.23 | 0.23 | 0.23 | 0.25 | 0.26 | 0.26 | 0.28 | 0.28 | 0.30 | 0.29 | 0.31 | 0.31 | 0.32 |
| X/100 | 0.28 | 0.28 | 0.28 | 0.28 | 0.28 | 0.28 | 0.27 | 0.28 | 0.27 | 0.27 | 0.26 | 0.26 | 0.26 | 0.25 | 0.25 | 0.25 | 0.24 | 0.24 |
|  | 0.13 | 0.13 | 0.13 | 0.13 | 0.13 | 0.13 | 0.13 | 0.13 | 0.13 | 0.13 | 0.13 | 0.13 | 0.13 | 0.13 | 0.13 | 0.13 | 0.13 | 0.13 |
| X2/10000 | 0.09 | 0.10 | 0.10 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.07 | 0.07 |
|  | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.07 | 0.07 | 0.07 |
| Spouse | 0.88 | 0.88 | 0.86 | 0.87 | 0.85 | 0.86 | 0.86 | 0.87 | 0.86 | 0.85 | 0.84 | 0.84 | 0.84 | 0.82 | 0.80 | 0.80 | 0.79 | 0.76 |
|  | 0.32 | 0.32 | 0.35 | 0.33 | 0.35 | 0.35 | 0.35 | 0.34 | 0.35 | 0.36 | 0.37 | 0.37 | 0.36 | 0.39 | 0.40 | 0.40 | 0.41 | 0.43 |
| Nspouse | 0.07 | 0.07 | 0.10 | 0.09 | 0.10 | 0.10 | 0.09 | 0.08 | 0.09 | 0.10 | 0.11 | 0.11 | 0.10 | 0.11 | 0.12 | 0.12 | 0.12 | 0.14 |
|  | 0.25 | 0.26 | 0.29 | 0.28 | 0.30 | 0.30 | 0.29 | 0.27 | 0.28 | 0.30 | 0.31 | 0.31 | 0.30 | 0.31 | 0.33 | 0.33 | 0.33 | 0.35 |
| Private | 0.81 | 0.80 | 0.82 | 0.82 | 0.81 | 0.80 | 0.78 | 0.79 | 0.76 | 0.77 | 0.77 | 0.77 | 0.76 | 0.77 | 0.77 | 0.79 | 0.79 | 0.78 |
|  | 0.39 | 0.40 | 0.38 | 0.38 | 0.39 | 0.40 | 0.41 | 0.41 | 0.42 | 0.42 | 0.42 | 0.42 | 0.43 | 0.42 | 0.42 | 0.41 | 0.40 | 0.41 |
| South | 0.51 | 0.52 | 0.55 | 0.54 | 0.52 | 0.50 | 0.53 | 0.55 | 0.53 | 0.52 | 0.53 | 0.52 | 0.52 | 0.57 | 0.56 | 0.55 | 0.58 | 0.58 |
|  | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.49 | 0.50 | 0.50 | 0.49 | 0.49 |
| City | 0.60 | 0.56 | 0.57 | 0.58 | 0.55 | 0.58 | 0.57 | 0.55 | 0.55 | 0.58 | 0.56 | 0.58 | 0.56 | 0.50 | 0.50 | 0.51 | 0.50 | 0.50 |
|  | 0.49 | 0.50 | 0.50 | 0.49 | 0.50 | 0.49 | 0.50 | 0.50 | 0.50 | 0.49 | 0.50 | 0.49 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 |

Spouse: Marital status dummy $=1$ if married, spouse present. Nspouse: Marital status dummy $=1$ if neither married with spouse present or
never married. Private: Class of worker dummy $=1$ if works for private firm or is self-employed. South: Region dummy $=1$ if south.
Ccity: Central city metropolitan statistical area status dummy $=1$ if central city.
IHS: Inc. High School, dummy = 1 if Educ $<12$; IC: Inc. College, dummy $=1$ if $12<$ Educ $<16 ; \mathrm{C}+$ : College or more, dummy $=1$ if Educ $>=16$.
First line has the mean of the variable and the second its standard deviation.

Table 1. Descriptive statistics of variables. (Continuation)
Black Males

| Year | 81 | 82 | 83 | 84 | 85 | 86 | 87 | 88 | 89 | 90 | 91 | 92 | 93 | 94 | 95 | 96 | 97 | 98 |
| :--- | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: |
| IHS | 0.37 | 0.35 | 0.34 | 0.31 | 0.30 | 0.27 | 0.27 | 0.26 | 0.26 | 0.24 | 0.23 | 0.21 | 0.18 | 0.16 | 0.14 | 0.15 | 0.15 | 0.13 |
|  | 0.48 | 0.48 | 0.47 | 0.46 | 0.46 | 0.44 | 0.44 | 0.44 | 0.44 | 0.43 | 0.42 | 0.41 | 0.39 | 0.37 | 0.35 | 0.36 | 0.36 | 0.34 |
| IC | 0.16 | 0.17 | 0.16 | 0.17 | 0.18 | 0.19 | 0.18 | 0.19 | 0.19 | 0.21 | 0.20 | 0.22 | 0.25 | 0.26 | 0.27 | 0.27 | 0.29 | 0.28 |
|  | 0.37 | 0.38 | 0.37 | 0.37 | 0.38 | 0.39 | 0.38 | 0.39 | 0.39 | 0.41 | 0.40 | 0.42 | 0.43 | 0.44 | 0.44 | 0.45 | 0.45 | 0.45 |
| C+ | 0.11 | 0.13 | 0.14 | 0.15 | 0.15 | 0.14 | 0.14 | 0.15 | 0.14 | 0.15 | 0.15 | 0.15 | 0.16 | 0.17 | 0.18 | 0.16 | 0.16 | 0.18 |
|  | 0.32 | 0.34 | 0.34 | 0.36 | 0.35 | 0.35 | 0.35 | 0.36 | 0.35 | 0.35 | 0.35 | 0.36 | 0.37 | 0.37 | 0.38 | 0.37 | 0.37 | 0.38 |
| X/100 | 0.24 | 0.23 | 0.24 | 0.23 | 0.23 | 0.23 | 0.23 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.23 | 0.22 | 0.22 |
|  | 0.13 | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 |
| X2/10000 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 |
|  | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.06 | 0.06 | 0.07 | 0.07 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 |
| Spouse | 0.76 | 0.78 | 0.77 | 0.76 | 0.75 | 0.73 | 0.74 | 0.73 | 0.57 | 0.57 | 0.56 | 0.55 | 0.55 | 0.55 | 0.55 | 0.54 | 0.53 | 0.54 |
|  | 0.43 | 0.41 | 0.42 | 0.43 | 0.43 | 0.44 | 0.44 | 0.44 | 0.49 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 |
| Nspouse | 0.14 | 0.12 | 0.13 | 0.13 | 0.13 | 0.13 | 0.12 | 0.13 | 0.19 | 0.19 | 0.19 | 0.20 | 0.17 | 0.18 | 0.19 | 0.20 | 0.19 | 0.18 |
|  | 0.35 | 0.33 | 0.34 | 0.34 | 0.33 | 0.34 | 0.33 | 0.34 | 0.40 | 0.39 | 0.40 | 0.40 | 0.38 | 0.38 | 0.39 | 0.40 | 0.39 | 0.39 |
| Private | 0.78 | 0.76 | 0.75 | 0.76 | 0.77 | 0.77 | 0.78 | 0.76 | 0.74 | 0.76 | 0.76 | 0.78 | 0.76 | 0.75 | 0.74 | 0.77 | 0.78 | 0.79 |
|  | 0.41 | 0.42 | 0.43 | 0.42 | 0.42 | 0.42 | 0.42 | 0.43 | 0.44 | 0.43 | 0.42 | 0.42 | 0.43 | 0.43 | 0.44 | 0.42 | 0.42 | 0.41 |
| South | 0.58 | 0.57 | 0.57 | 0.57 | 0.58 | 0.54 | 0.57 | 0.57 | 0.59 | 0.54 | 0.55 | 0.53 | 0.54 | 0.53 | 0.53 | 0.53 | 0.52 | 0.55 |
|  | 0.49 | 0.49 | 0.49 | 0.49 | 0.49 | 0.50 | 0.50 | 0.50 | 0.49 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 |
| City | 0.50 | 0.49 | 0.48 | 0.49 | 0.50 | 0.50 | 0.48 | 0.50 | 0.47 | 0.47 | 0.48 | 0.48 | 0.48 | 0.47 | 0.47 | 0.48 | 0.49 | 0.48 |
|  | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 |

Spouse: Marital status dummy $=1$ if married, spouse present. Nspouse: Marital status dummy $=1$ if neither married with spouse present or
never married. Private: Class of worker dummy $=1$ if works for private firm or is self-employed. South: Region dummy $=1$ if south.
Ccity: Central city metropolitan statistical area status dummy $=1$ if central city.
IHS: Inc. High School, dummy $=1$ if Educ $<12$; IC: Inc. College, dummy $=1$ if $12<$ Educ $<16 ;$ C + : College or more, dummy $=1$ if Educ $>=16$.
First line has the mean of the variable and the second its standard deviation.

Table 1. Descriptive statistics of variables. (Continuation)
White Males

| Year | 64 | 65 | 66 | 67 | 68 | 69 | 70 | 71 | 72 | 73 | 74 | 75 | 76 | 77 | 78 | 79 | 80 | 81 |
| :--- | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: |
| IHS | 0.44 | 0.42 | 0.42 | 0.39 | 0.40 | 0.38 | 0.35 | 0.33 | 0.33 | 0.31 | 0.28 | 0.26 | 0.27 | 0.26 | 0.24 | 0.23 | 0.22 | 0.20 |
|  | 0.50 | 0.49 | 0.49 | 0.49 | 0.49 | 0.49 | 0.48 | 0.47 | 0.47 | 0.46 | 0.45 | 0.44 | 0.44 | 0.44 | 0.43 | 0.42 | 0.41 | 0.40 |
| IC | 0.10 | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 | 0.12 | 0.13 | 0.13 | 0.13 | 0.15 | 0.16 | 0.16 | 0.17 | 0.17 | 0.18 | 0.17 | 0.18 |
|  | 0.31 | 0.31 | 0.31 | 0.32 | 0.32 | 0.31 | 0.33 | 0.34 | 0.33 | 0.34 | 0.36 | 0.37 | 0.36 | 0.37 | 0.38 | 0.39 | 0.38 | 0.38 |
| C+ | 0.13 | 0.14 | 0.14 | 0.15 | 0.14 | 0.15 | 0.15 | 0.15 | 0.16 | 0.17 | 0.19 | 0.21 | 0.21 | 0.21 | 0.22 | 0.21 | 0.24 | 0.25 |
|  | 0.34 | 0.35 | 0.35 | 0.36 | 0.35 | 0.36 | 0.35 | 0.36 | 0.37 | 0.38 | 0.40 | 0.41 | 0.41 | 0.40 | 0.41 | 0.41 | 0.43 | 0.43 |
| X/100 | 0.26 | 0.26 | 0.26 | 0.26 | 0.26 | 0.25 | 0.25 | 0.26 | 0.25 | 0.25 | 0.24 | 0.24 | 0.24 | 0.24 | 0.24 | 0.23 | 0.23 | 0.23 |
|  | 0.12 | 0.12 | 0.12 | 0.12 | 0.13 | 0.13 | 0.12 | 0.12 | 0.13 | 0.13 | 0.12 | 0.12 | 0.13 | 0.13 | 0.13 | 0.13 | 0.13 | 0.12 |
| X2/10000 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 |
|  | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.06 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.06 |
| Spouse | 0.93 | 0.94 | 0.93 | 0.94 | 0.93 | 0.92 | 0.92 | 0.93 | 0.93 | 0.92 | 0.92 | 0.91 | 0.92 | 0.91 | 0.91 | 0.90 | 0.88 | 0.87 |
|  | 0.26 | 0.24 | 0.26 | 0.23 | 0.26 | 0.26 | 0.27 | 0.25 | 0.26 | 0.27 | 0.27 | 0.28 | 0.28 | 0.28 | 0.29 | 0.30 | 0.32 | 0.33 |
| Nspouse | 0.02 | 0.03 | 0.03 | 0.03 | 0.03 | 0.04 | 0.03 | 0.03 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.05 | 0.06 | 0.06 |
|  | 0.16 | 0.16 | 0.18 | 0.16 | 0.18 | 0.19 | 0.18 | 0.18 | 0.18 | 0.19 | 0.19 | 0.20 | 0.20 | 0.20 | 0.20 | 0.22 | 0.24 | 0.24 |
| Private | 0.84 | 0.86 | 0.85 | 0.84 | 0.84 | 0.84 | 0.85 | 0.83 | 0.84 | 0.83 | 0.83 | 0.82 | 0.84 | 0.83 | 0.84 | 0.83 | 0.83 | 0.83 |
|  | 0.36 | 0.35 | 0.35 | 0.37 | 0.36 | 0.36 | 0.36 | 0.38 | 0.37 | 0.37 | 0.38 | 0.39 | 0.37 | 0.38 | 0.37 | 0.37 | 0.37 | 0.38 |
| South | 0.25 | 0.26 | 0.26 | 0.27 | 0.27 | 0.26 | 0.28 | 0.27 | 0.28 | 0.29 | 0.27 | 0.29 | 0.30 | 0.27 | 0.27 | 0.27 | 0.28 | 0.28 |
|  | 0.44 | 0.44 | 0.44 | 0.44 | 0.44 | 0.44 | 0.45 | 0.44 | 0.45 | 0.45 | 0.45 | 0.45 | 0.46 | 0.44 | 0.45 | 0.45 | 0.45 | 0.45 |
| City | 0.30 | 0.28 | 0.28 | 0.28 | 0.25 | 0.25 | 0.25 | 0.24 | 0.27 | 0.25 | 0.24 | 0.25 | 0.24 | 0.19 | 0.19 | 0.18 | 0.18 | 0.18 |
|  | 0.46 | 0.45 | 0.45 | 0.45 | 0.43 | 0.43 | 0.43 | 0.43 | 0.44 | 0.43 | 0.43 | 0.43 | 0.42 | 0.39 | 0.39 | 0.39 | 0.39 | 0.38 |

Spouse: Marital status dummy = 1 if married, spouse present. Nspouse: Marital status dummy $=1$ if neither married with spouse present or
never married. Private: Class of worker dummy $=1$ if works for private firm or is self-employed. South: Region dummy $=1$ if south.
Ccity: Central city metropolitan statistical area status dummy $=1$ if central city.
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First line has the mean of the variable and the second its standard deviation.

Table 1. Descriptive statistics of variables. (Continuation)
White Males

| Year | 81 | 82 | 83 | 84 | 85 | 86 | 87 | 88 | 89 | 90 | 91 | 92 | 93 | 94 | 95 | 96 | 97 | 98 |
| :--- | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: |
| IHS | 0.20 | 0.20 | 0.18 | 0.19 | 0.17 | 0.17 | 0.17 | 0.16 | 0.17 | 0.16 | 0.15 | 0.12 | 0.13 | 0.12 | 0.12 | 0.13 | 0.13 | 0.12 |
|  | 0.40 | 0.40 | 0.39 | 0.39 | 0.38 | 0.37 | 0.37 | 0.36 | 0.37 | 0.37 | 0.36 | 0.33 | 0.34 | 0.33 | 0.33 | 0.33 | 0.34 | 0.33 |
| IC | 0.18 | 0.18 | 0.18 | 0.18 | 0.19 | 0.20 | 0.19 | 0.20 | 0.19 | 0.19 | 0.20 | 0.25 | 0.25 | 0.27 | 0.25 | 0.26 | 0.27 | 0.27 |
|  | 0.38 | 0.38 | 0.39 | 0.39 | 0.39 | 0.40 | 0.39 | 0.40 | 0.39 | 0.39 | 0.40 | 0.43 | 0.43 | 0.45 | 0.43 | 0.44 | 0.44 | 0.44 |
| C+ | 0.25 | 0.26 | 0.27 | 0.26 | 0.26 | 0.25 | 0.27 | 0.26 | 0.26 | 0.27 | 0.26 | 0.25 | 0.26 | 0.26 | 0.28 | 0.26 | 0.26 | 0.26 |
|  | 0.43 | 0.44 | 0.44 | 0.44 | 0.44 | 0.44 | 0.44 | 0.44 | 0.44 | 0.44 | 0.44 | 0.43 | 0.44 | 0.44 | 0.45 | 0.44 | 0.44 | 0.44 |
| X/100 | 0.23 | 0.23 | 0.23 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.23 | 0.22 | 0.22 | 0.23 |
|  | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 |
| X2/10000 | 0.07 | 0.07 | 0.07 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 |
|  | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 |
| Spouse | 0.87 | 0.88 | 0.86 | 0.87 | 0.85 | 0.85 | 0.85 | 0.85 | 0.73 | 0.73 | 0.72 | 0.70 | 0.72 | 0.72 | 0.71 | 0.70 | 0.70 | 0.69 |
|  | 0.33 | 0.33 | 0.34 | 0.34 | 0.36 | 0.36 | 0.36 | 0.36 | 0.44 | 0.44 | 0.45 | 0.46 | 0.45 | 0.45 | 0.45 | 0.46 | 0.46 | 0.46 |
| Nspouse | 0.06 | 0.06 | 0.06 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.11 | 0.11 | 0.12 | 0.13 | 0.12 | 0.12 | 0.13 | 0.13 | 0.13 | 0.14 |
|  | 0.24 | 0.24 | 0.24 | 0.25 | 0.26 | 0.26 | 0.26 | 0.26 | 0.31 | 0.32 | 0.32 | 0.33 | 0.33 | 0.32 | 0.34 | 0.33 | 0.34 | 0.35 |
| Private | 0.83 | 0.84 | 0.83 | 0.84 | 0.84 | 0.85 | 0.85 | 0.85 | 0.83 | 0.83 | 0.83 | 0.84 | 0.84 | 0.83 | 0.84 | 0.84 | 0.85 | 0.85 |
|  | 0.38 | 0.37 | 0.37 | 0.36 | 0.37 | 0.36 | 0.36 | 0.36 | 0.38 | 0.37 | 0.37 | 0.37 | 0.37 | 0.38 | 0.37 | 0.36 | 0.36 | 0.36 |
| South | 0.28 | 0.27 | 0.28 | 0.29 | 0.29 | 0.28 | 0.28 | 0.28 | 0.30 | 0.29 | 0.28 | 0.27 | 0.27 | 0.27 | 0.30 | 0.28 | 0.30 | 0.28 |
|  | 0.45 | 0.44 | 0.45 | 0.45 | 0.45 | 0.45 | 0.45 | 0.45 | 0.46 | 0.45 | 0.45 | 0.45 | 0.45 | 0.45 | 0.46 | 0.45 | 0.46 | 0.45 |
| City | 0.18 | 0.19 | 0.19 | 0.18 | 0.18 | 0.20 | 0.19 | 0.18 | 0.19 | 0.19 | 0.20 | 0.20 | 0.20 | 0.19 | 0.18 | 0.20 | 0.20 | 0.21 |
|  | 0.38 | 0.39 | 0.39 | 0.38 | 0.39 | 0.40 | 0.39 | 0.39 | 0.39 | 0.39 | 0.40 | 0.40 | 0.40 | 0.39 | 0.38 | 0.40 | 0.40 | 0.41 |

Spouse: Marital status dummy = 1 if married, spouse present. Nspouse: Marital status dummy $=1$ if neither married with spouse present or
never married. Private: Class of worker dummy $=1$ if works for private firm or is self-employed. South: Region dummy $=1$ if south.
Ccity: Central city metropolitan statistical area status dummy $=1$ if central city.
IHS: Inc. High School, dummy = 1 if Educ $<12$; IC: Inc. College, dummy $=1$ if $12<$ Educ $<16 ; \mathrm{C}+$ : College or more, dummy $=1$ if Educ $>=16$.
First line has the mean of the variable and the second its standard deviation.

Table 2. Estimated coefficients of the standard log wage regression.
Black Males

| Year | 64 | 65 | 66 | 67 | 68 | 69 | 70 | 71 | 72 | 73 | 74 | 75 | 76 | 77 | 78 | 79 | 80 | 81 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Constant | 1.674 | 1.716 | 1.637 | 1.565 | 1.650 | 1.732 | 1.787 | 1.862 | 1.758 | 1.651 | 1.709 | 1.800 | 1.781 | 1.740 | 1.659 | 1.814 | 1.507 | 1.641 |
|  | 18.175 | 19.653 | 23.723 | 17.277 | 26.322 | 27.408 | 26.045 | 29.931 | 28.043 | 22.610 | 24.697 | 26.661 | 26.227 | 31.983 | 28.997 | 28.118 | 27.202 | 29.675 |
| IHS | -0.106 | -0.043 | -0.086 | -0.101 | -0.094 | -0.092 | -0.097 | -0.080 | -0.045 | -0.108 | -0.202 | -0.116 | -0.098 | -0.106 | -0.125 | -0.146 | -0.136 | -0.229 |
|  | -2.539 | -1.196 | -3.627 | -3.539 | -4.467 | -4.225 | -4.470 | -3.558 | -1.953 | -4.737 | -8.724 | -4.014 | -3.580 | -4.611 | -4.785 | -5.907 | -5.301 | -10.000 |
| IC | 0.149 | -0.024 | 0.070 | 0.121 | 0.104 | 0.102 | 0.069 | 0.071 | 0.052 | 0.040 | 0.028 | 0.042 | 0.066 | 0.029 | 0.068 | 0.027 | 0.097 | 0.073 |
|  | 2.785 | -0.388 | 1.721 | 2.274 | 2.753 | 2.813 | 2.161 | 2.231 | 1.277 | 1.160 | 0.801 | 1.287 | 2.021 | 1.054 | 2.163 | 0.792 | 3.760 | 2.878 |
| C+ | 0.217 | 0.246 | 0.271 | 0.236 | 0.233 | 0.225 | 0.145 | 0.235 | 0.255 | 0.268 | 0.220 | 0.173 | 0.166 | 0.271 | 0.373 | 0.264 | 0.314 | 0.156 |
|  | 3.535 | 4.753 | 5.18 | 3.217 | 5.420 | 5.213 | 3.406 | 5.582 | 6.257 | 5.047 | 6.036 | 4.040 | 3.450 | 8.429 | 11.773 | 6.657 | 9.035 | 4.741 |
| X/100 | 0.626 | 0.195 | 0.886 | 1.512 | 1.482 | 1.280 | 0.791 | 1.202 | 1.164 | 1.673 | 1.724 | 2.038 | 1.807 | 1.668 | 2.409 | 1.527 | 2.630 | 2.241 |
|  | 1.195 | 0.408 | 2.815 | 3.548 | 4.928 | 4.329 | 2.492 | 3.942 | 3.554 | 4.779 | 4.508 | 5.460 | 4.930 | 5.352 | 7.025 | 4.448 | 7.752 | 6.351 |
| X2/10000 | -1.371 | -0.590 | -1.070 | -2.898 | -3.099 | -2.456 | -1.906 | -2.653 | -2.755 | -2.875 | -3.056 | -4.249 | -3.254 | -3.227 | -4.588 | -3.063 | -5.293 | -3.993 |
|  | -1.541 | -0.720 | -2.078 | -4.107 | -6.249 | -5.091 | -3.491 | -5.203 | -4.835 | -4.766 | -4.389 | -6.553 | -4.995 | -5.763 | -7.637 | -5.123 | -8.574 | -5.968 |
| Spouse | 0.16 | 0.186 | 0.163 | 0.217 | 0.215 | 0.184 | 0.252 | 0.153 | 0.263 | 0.271 | 0.181 | 0.129 | 0.119 | 0.214 | 0.149 | 0.253 | 0.258 | 0.215 |
|  | 2.652 | 3.198 | 3.147 | 3.484 | 4.398 | 4.276 | 4.887 | 3.444 | 6.119 | 5.495 | 3.623 | 2.649 | 2.363 | 5.724 | 3.779 | 5.521 | 7.119 | 6.119 |
| Nspouse | 0.082 | 0.080 | 0.082 | 0.174 | 0.108 | 0.077 | 0.134 | 0.007 | 0.195 | 0.154 | 0.083 | 0.019 | 0.070 | 0.135 | 0.026 | 0.099 | 0.178 | 0.105 |
|  | 0.847 | 1.013 | 1.358 | 2.377 | 1.922 | 1.520 | 2.126 | 0.122 | 3.616 | 2.652 | 1.343 | 0.311 | 1.139 | 3.004 | 0.553 | 1.836 | 4.045 | 2.380 |
| Private | -0.048 | -0.095 | -0.107 | -0.066 | -0.060 | -0.052 | -0.031 | -0.076 | -0.097 | -0.072 | -0.004 | 0.026 | -0.055 | -0.092 | -0.046 | -0.083 | -0.023 | -0.082 |
|  | -1.607 | -3.095 | -4.812 | -2.290 | -3.227 | -2.453 | -1.542 | -3.908 | -4.704 | -2.979 | -0.211 | 1.092 | -2.432 | -4.708 | -2.201 | -3.456 | -1.032 | -4.116 |
| South | -0.416 | -0.412 | -0.406 | -0.412 | -0.334 | -0.350 | -0.309 | -0.321 | -0.293 | -0.233 | -0.181 | -0.206 | -0.236 | -0.211 | -0.133 | -0.226 | -0.140 | -0.146 |
|  | -14.195 | -15.270 | -22.087 | -16.967 | -18.152 | -19.000 | -17.240 | -18.314 | -15.103 | -11.038 | -8.597 | -9.048 | -10.995 | -11.202 | -6.348 | -10.570 | -7.102 | -8.066 |
| City | 0.131 | 0.170 | 0.177 | 0.189 | 0.104 | 0.101 | 0.085 | 0.116 | 0.107 | 0.106 | 0.141 | 0.055 | 0.147 | 0.107 | 0.086 | 0.031 | 0.098 | 0.063 |
|  | 4.357 | 6.032 | 9.234 | 7.458 | 5.658 | 5.412 | 4.630 | 6.576 | 5.317 | 4.981 | 6.488 | 2.353 | 6.774 | 5.821 | 4.184 | 1.462 | 5.026 | 3.517 |


| N | 1,833 | 1,992 | 4,185 | 2,635 | 3,928 | 3,841 | 3,707 | 3,629 | 3,362 | 3,107 | 3,006 | 2,697 | 2,881 | 3,341 | 3,387 | 3,247 | 3,622 | 3,622 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| RSQ | 0.193 | 0.185 | 0.191 | 0.217 | 0.189 | 0.180 | 0.152 | 0.204 | 0.172 | 0.140 | 0.140 | 0.108 | 0.129 | 0.148 | 0.123 | 0.127 | 0.127 | 0.129 |

Spouse: Marital status dummy $=1$ if married, spouse present. Nspouse: Marital status dummy $=1$ if neither married with spouse present or never married.
Private: Class of worker dummy $=1$ if works for private firm or is self-employed. South: Region dummy $=1$ if south.
Ccity: Central city metropolitan statistical area status dummy $=1$ if central city.
IHS: Inc. High School, dummy $=1$ if Educ $<12$; IC: Inc. College, dummy $=1$ if $12<$ Educ $<16$; $\mathrm{C}+$ : College or more, dummy $=1$ if Educ $>=16$.

* t statistics.

Table 2. Estimated coefficients of the standard log wage regression. (Continuation)
Black Males

| Year | 81 | 82 | 83 | 84 | 85 | 86 | 87 | 88 | 89 | 90 | 91 | 92 | 93 | 94 | 95 | 96 | 97 | 98 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Constant | 1.641 | 1.743 | 1.650 | 1.563 | 1.477 | 1.587 | 1.522 | 1.509 | 1.390 | 1.498 | 1.360 | 1.442 | 1.405 | 1.419 | 1.424 | 1.440 | 1.593 | 1.519 |
|  | 29.675 | 29.697 | 28.550 | 25.369 | 25.593 | 29.721 | 29.719 | 26.748 | 22.939 | 24.879 | 23.729 | 22.998 | 23.648 | 21.758 | 22.215 | 20.715 | 22.026 | 22.078 |
| IHS | -0.229 | -0.171 | -0.119 | -0.224 | -0.206 | -0.124 | -0.114 | -0.125 | -0.188 | -0.225 | -0.171 | -0.183 | -0.185 | -0.138 | -0.092 | -0.253 | -0.197 | -0.232 |
|  | -10.000 | -6.718 | -4.510 | -8.436 | -7.814 | -4.429 | -4.274 | -4.679 | -5.606 | -6.414 | -4.994 | -5.220 | -5.431 | -3.673 | -1.964 | -6.376 | -5.070 | -5.363 |
| IC | 0.073 | 0.027 | 0.108 | 0.154 | 0.112 | 0.124 | 0.114 | 0.133 | 0.182 | 0.131 | 0.191 | 0.116 | 0.176 | 0.212 | 0.193 | 0.138 | 0.171 | 0.174 |
|  | 2.878 | 1.019 | 3.724 | 5.144 | 3.869 | 4.909 | 4.469 | 4.978 | 5.600 | 4.500 | 6.318 | 3.866 | 6.234 | 7.500 | 6.503 | 4.505 | 5.687 | 5.692 |
| C+ | 0.156 | 0.235 | 0.246 | 0.338 | 0.378 | 0.393 | 0.288 | 0.361 | 0.369 | 0.398 | 0.413 | 0.406 | 0.458 | 0.487 | 0.393 | 0.445 | 0.328 | 0.373 |
|  | 4.741 | 6.357 | 7.269 | 9.871 | 12.770 | 13.473 | 9.763 | 10.877 | 10.146 | 11.833 | 12.135 | 10.341 | 13.710 | 13.909 | 11.068 | 10.674 | 8.609 | 10.103 |
| X/100 | 2.241 | 1.086 | 2.175 | 2.364 | 2.597 | 2.471 | 3.679 | 2.609 | 3.400 | 2.836 | 3.032 | 2.251 | 2.458 | 2.049 | 2.830 | 2.351 | 1.315 | 1.803 |
|  | 6.351 | 2.834 | 6.340 | 5.805 | 7.617 | 6.688 | 10.310 | 7.228 | 7.960 | 7.117 | 7.415 | 5.150 | 5.566 | 4.038 | 6.103 | 4.926 | 2.488 | 3.618 |
| X2/10000 | -3.993 | -2.151 | -4.085 | -3.349 | -3.949 | -3.843 | -6.593 | -4.278 | -5.359 | -4.136 | -4.729 | -3.259 | -3.222 | -2.858 | -4.282 | -2.830 | -1.244 | -2.285 |
|  | -5.968 | -3.037 | -6.799 | -4.606 | -6.445 | -5.276 | -9.497 | -6.335 | -6.747 | -5.379 | -6.083 | -3.900 | -3.726 | -2.946 | -4.827 | -3.092 | -1.212 | -2.290 |
| Spouse | 0.215 | 0.212 | 0.135 | 0.104 | 0.163 | 0.127 | 0.188 | 0.197 | 0.209 | 0.197 | 0.220 | 0.257 | 0.207 | 0.228 | 0.167 | 0.189 | 0.164 | 0.139 |
|  | 6.119 | 5.905 | 3.599 | 2.623 | 5.031 | 4.233 | 6.277 | 6.281 | 6.396 | 6.933 | 7.493 | 8.467 | 7.477 | 7.648 | 5.057 | 5.544 | 5.213 | 4.444 |
| Nspouse | 0.105 | 0.118 | 0.080 | 0.060 | 0.092 | 0.033 | 0.050 | 0.134 | 0.036 | 0.009 | 0.110 | 0.137 | 0.107 | 0.058 | 0.044 | 0.074 | 0.089 | 0.047 |
|  | 2.380 | 2.517 | 1.675 | 1.259 | 2.217 | 0.847 | 1.274 | 3.253 | 0.896 | 0.247 | 2.928 | 3.674 | 2.959 | 1.514 | 1.073 | 1.829 | 2.279 | 1.168 |
| Private | -0.082 | -0.080 | -0.041 | -0.017 | -0.035 | -0.053 | -0.081 | -0.113 | -0.046 | -0.097 | -0.058 | -0.089 | -0.059 | -0.064 | -0.098 | -0.087 | -0.111 | -0.056 |
|  | -4.116 | -3.712 | -1.888 | -0.677 | -1.559 | -2.453 | -3.941 | -5.027 | -1.652 | -3.511 | -2.133 | -2.960 | -2.215 | -2.370 | -3.375 | -2.844 | -3.716 | -1.780 |
| South | -0.146 | -0.141 | -0.143 | -0.149 | -0.113 | -0.137 | -0.189 | -0.121 | -0.215 | -0.208 | -0.197 | -0.176 | -0.214 | -0.164 | -0.135 | -0.127 | -0.119 | -0.057 |
|  | -8.066 | -7.000 | -6.937 | -6.817 | -5.367 | -7.093 | -9.732 | -6.005 | -8.677 | -9.043 | -8.255 | -7.205 | -9.017 | -6.949 | -5.430 | -4.926 | -4.772 | -2.245 |
| City | 0.063 | 0.058 | 0.059 | 0.028 | 0.022 | -0.020 | -0.047 | 0.020 | 0.031 | -0.014 | 0.044 | 0.008 | -0.018 | -0.007 | -0.027 | -0.046 | -0.018 | -0.042 |
|  | 3.517 | 2.885 | 2.896 | 1.284 | 1.082 | -1.041 | -2.412 | 1.005 | 1.269 | -0.622 | 1.889 | 0.332 | -0.796 | -0.280 | -1.087 | -1.783 | -0.738 | -1.687 |


| N | 3,622 | 3,280 | 3,160 | 3,326 | 3,407 | $3,523$ | $3,551$ | $3,475$ | $2,201$ | $2,532$ | $2,485$ | $2,490$ | $2,420$ | $2,252$ | $2,324$ | $2,014$ | $2,108$ | $2,078$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| RSQ | 0.129 | 0.102 | 0.092 | 0.118 | 0.124 | $0.112$ | $0.134$ | $0.118$ | $0.179$ | $0.182$ | $0.175$ | $0.160$ | $0.196$ | $0.196$ | $0.131$ | $0.171$ | $0.122$ | $0.120$ |

Spouse: Marital status dummy $=1$ if married, spouse present. Nspouse: Marital status dummy $=1$ if neither married with spouse present or never married.
Private: Class of worker dummy $=1$ if works for private firm or is self-employed. South: Region dummy $=1$ if south.
Ccity: Central city metropolitan statistical area status dummy $=1$ if central city.
IHS: Inc. High School, dummy = 1 if Educ<12; IC: Inc. College, dummy $=1$ if $12<$ Educ $<16 ;$ C+: College or more, dummy $=1$ if Educ $>=16$.

* t statistics.

Table 2. Estimated coefficients of the standard log wage regression. (Continuation)
White Males

| Year | 64 | 65 | 66 | 67 | 68 | 69 | 70 | 71 | 72 | 73 | 74 | 75 | 76 | 77 | 78 | 79 | 80 | 81 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Constant | 1.728 | 1.631 | 1.632 | 1.734 | 1.669 | 1.848 | 1.813 | 1.805 | 1.788 | 1.774 | 1.757 | 1.584 | 1.645 | 1.746 | 1.625 | 1.652 | 1.583 | 1.480 |
|  | 27.824 | 25.318 | 24.244 | 26.557 | 31.422 | 29.104 | 33.379 | 27.384 | 30.357 | 26.316 | 28.753 | 26.056 | 30.064 | 34.109 | 30.492 | 31.529 | 32.774 | 29.667 |
| IHS | -0.120 | -0.126 | -0.186 | -0.163 | -0.165 | -0.148 | -0.120 | -0.146 | -0.129 | -0.120 | -0.175 | -0.152 | -0.205 | -0.190 | -0.199 | -0.190 | -0.181 | -0.174 |
|  | -5.733 | -5.976 | -9.113 | -7.679 | -8.930 | -7.541 | -6.040 | -6.952 | -6.450 | -5.416 | -8.159 | -6.351 | -9.549 | -8.939 | -9.110 | -8.464 | -7.785 | -7.446 |
| IC | 0.096 | 0.116 | 0.111 | 0.058 | 0.090 | 0.092 | 0.064 | 0.075 | 0.066 | 0.081 | 0.066 | 0.094 | 0.054 | 0.059 | 0.095 | 0.024 | 0.088 | 0.067 |
|  | 3.194 | 3.785 | 4.387 | 2.028 | 3.826 | 3.407 | 2.819 | 2.888 | 2.838 | 3.219 | 2.809 | 3.774 | 2.357 | 2.677 | 4.198 | 1.090 | 3.789 | 2.917 |
| C+ | 0.203 | 0.164 | 0.237 | 0.234 | 0.228 | 0.245 | 0.232 | 0.200 | 0.212 | 0.236 | 0.194 | 0.209 | 0.295 | 0.230 | 0.249 | 0.208 | 0.232 | 0.196 |
|  | 6.604 | 5.236 | 7.983 | 8.471 | 8.961 | 9.475 | 9.070 | 8.130 | 8.510 | 9.077 | 8.143 | 8.790 | 13.031 | 10.479 | 11.116 | 9.262 | 10.171 | 9.093 |
| X/100 | 1.609 | 2.057 | 2.575 | 1.744 | 2.05 | 1.718 | 1.950 | 2.134 | 2.247 | 2.376 | 2.124 | 3.103 | 3.287 | 3.263 | 3.092 | 2.978 | 2.700 | 2.837 |
|  | 5.309 | 6.225 | 7.940 | 5.250 | 7.386 | 5.680 | 6.696 | 6.898 | 7.644 | 7.843 | 6.324 | 9.181 | 10.945 | 11.503 | 9.945 | 10.073 | 8.957 | 9.290 |
| X2/10000 | -2.879 | -3.576 | -4.672 | -3.125 | -3.621 | -2.986 | -3.650 | -4.104 | -4.045 | -4.300 | -3.523 | -5.517 | -5.683 | -5.783 | -5.368 | -5.126 | -4.508 | -5.185 |
|  | -5.123 | -5.877 | -7.799 | -4.988 | -7.057 | -5.180 | -6.525 | -6.955 | -7.176 | -7.387 | -5.197 | -8.075 | -9.474 | -10.458 | -8.655 | -8.647 | -7.577 | -8.501 |
| Spouse | 0.217 | 0.269 | 0.250 | 0.256 | 0.29 | 0.170 | 0.234 | 0.253 | 0.227 | 0.235 | 0.281 | 0.307 | 0.227 | 0.107 | 0.256 | 0.194 | 0.183 | 0.325 |
|  | 4.465 | 5.329 | 4.620 | 5.126 | 6.689 | 3.300 | 5.087 | 4.473 | 4.857 | 4.360 | 5.772 | 6.093 | 4.869 | 2.644 | 6.083 | 4.370 | 4.859 | 8.072 |
| Nspouse | 0.256 | 0.123 | 0.205 | 0.210 | 0.152 | 0.038 | 0.191 | 0.175 | 0.078 | 0.100 | 0.205 | 0.154 | 0.115 | 0.021 | 0.175 | 0.072 | 0.110 | 0.240 |
|  | 3.726 | 1.538 | 2.710 | 2.460 | 2.381 | 0.525 | 3.053 | 2.432 | 1.241 | 1.383 | 3.212 | 2.455 | 1.860 | 0.372 | 2.746 | 1.234 | 2.113 | 4.624 |
| Private | -0.031 | -0.032 | -0.021 | 0.015 | -0.010 | -0.019 | -0.013 | -0.018 | -0.014 | -0.027 | -0.017 | -0.001 | -0.033 | -0.031 | -0.049 | -0.005 | 0.024 | -0.001 |
|  | -1.527 | -1.394 | -0.976 | 0.760 | -0.526 | -0.980 | -0.650 | -0.902 | -0.746 | -1.244 | -0.850 | -0.043 | -1.675 | -1.716 | -2.490 | -0.293 | 1.270 | -0.059 |
| South | -0.207 | -0.186 | -0.189 | -0.195 | -0.162 | -0.153 | -0.164 | -0.193 | -0.195 | -0.134 | -0.135 | -0.117 | -0.121 | -0.106 | -0.066 | -0.088 | -0.092 | -0.082 |
|  | -10.132 | -8.548 | -9.953 | -9.760 | -8.967 | -8.193 | -9.168 | -10.132 | -10.356 | -6.979 | -7.436 | -6.115 | -6.831 | -5.829 | -3.756 | -5.011 | -5.055 | -4.508 |
| City | 0.077 | 0.071 | 0.058 | 0.071 | 0.065 | 0.063 | 0.013 | 0.004 | 0.036 | 0.042 | 0.006 | 0.000 | 0.014 | 0.027 | 0.059 | 0.036 | 0.021 | 0.012 |
|  | 4.491 | 3.796 | 3.165 | 3.797 | 3.988 | 3.645 | 0.764 | 0.234 | 2.100 | 2.215 | 0.326 | -0.010 | 0.730 | 1.443 | 2.960 | 1.875 | 1.060 | 0.636 |


| N | 4,428 | 4,423 | 4,477 | 4,566 | 4,510 | 4,575 | 4,481 | 4,365 | 4,377 | 4,304 | 4,436 | 4,104 | 5,029 | 5,051 | 4,924 | 5,024 | 5,109 | 5,000 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| RSQ | 0.076 | 0.071 | 0.115 | 0.085 | 0.108 | 0.085 | 0.084 | 0.093 | 0.094 | 0.077 | 0.078 | 0.089 | 0.112 | 0.088 | 0.098 | 0.077 | 0.072 | 0.086 |

Spouse: Marital status dummy $=1$ if married, spouse present. Nspouse: Marital status dummy $=1$ if neither married with spouse present or never married.
Private: Class of worker dummy $=1$ if works for private firm or is self-employed. South: Region dummy $=1$ if south.
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* t statistics.

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White Males

| Year | 81 | 82 | 83 | 84 | 85 | 86 | 87 | 88 | 89 | 90 | 91 | 92 | 93 | 94 | 95 | 96 | 97 | 98 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Constant | 1.480 | 1.527 | 1.601 | 1.598 | 1.609 | 1.622 | 1.527 | 1.591 | 1.543 | 1.484 | 1.534 | 1.489 | 1.475 | 1.452 | 1.494 | 1.402 | 1.473 | 1.473 |
|  | 29.667 | 30.483 | 31.948 | 31.035 | 33.107 | 32.907 | 29.877 | 32.659 | 37.552 | 35.766 | 33.575 | 35.969 | 33.595 | 31.021 | 33.196 | 30.676 | 31.675 | 31.823 |
| IHS | -0.174 | -0.192 | -0.226 | -0.261 | -0.250 | -0.199 | -0.231 | -0.238 | -0.304 | -0.235 | -0.312 | -0.287 | -0.275 | -0.278 | -0.289 | -0.314 | -0.300 | -0.323 |
|  | -7.446 | -7.757 | -8.611 | -10.160 | -9.378 | -7.300 | -8.423 | -8.315 | -11.615 | -9.306 | -12.004 | -10.177 | -10.392 | -9.751 | -10.087 | -11.453 | -10.806 | -11.904 |
| IC | 0.067 | 0.108 | 0.116 | 0.066 | 0.063 | 0.082 | 0.155 | 0.126 | 0.112 | 0.142 | 0.127 | 0.133 | 0.147 | 0.089 | 0.126 | 0.121 | 0.134 | 0.127 |
|  | 2.917 | 4.856 | 4.680 | 2.740 | 2.615 | 3.622 | 6.694 | 5.267 | 5.091 | 6.781 | 5.981 | 6.592 | 7.308 | 4.237 | 5.763 | 5.865 | 6.634 | 5.921 |
| C+ | 0.196 | 0.217 | 0.248 | 0.291 | 0.278 | 0.269 | 0.359 | 0.334 | 0.334 | 0.376 | 0.351 | 0.390 | 0.396 | 0.399 | 0.380 | 0.381 | 0.360 | 0.369 |
|  | 9.093 | 9.709 | 10.916 | 12.911 | 12.397 | 12.241 | 16.854 | 14.667 | 16.307 | 18.624 | 16.870 | 18.158 | 18.481 | 18.553 | 18.114 | 16.561 | 16.662 | 16.991 |
| X/100 | 2.837 | 3.277 | 2.394 | 2.609 | 2.715 | 3.058 | 2.632 | 3.055 | 2.703 | 2.797 | 2.446 | 2.490 | 2.166 | 2.414 | 2.342 | 2.941 | 2.420 | 2.594 |
|  | 9.290 | 10.403 | 7.419 | 7.445 | 8.216 | 8.749 | 8.181 | 8.950 | 9.087 | 9.034 | 7.151 | 8.169 | 6.858 | 7.350 | 7.097 | 9.301 | 7.322 | 7.857 |
| X2/10000 | -5.185 | -5.446 | -3.882 | -3.758 | -4.472 | -5.156 | -4.104 | -4.913 | -4.242 | -4.590 | -3.795 | -3.813 | -3.334 | -3.609 | -3.270 | -4.640 | -3.713 | -4.231 |
|  | -8.501 | -8.569 | -6.102 | -5.238 | -6.933 | -7.178 | -6.353 | -7.097 | -7.276 | -7.379 | -5.458 | -6.232 | -5.377 | -5.472 | -4.957 | -7.437 | -5.474 | -6.319 |
| Spouse | 0.32 | 0.200 | 0.241 | 0.130 | 0.210 | 0.187 | 0.236 | 0.139 | 0.192 | 0.201 | 0.200 | 0.257 | 0.269 | 0.246 | 0.226 | 0.210 | 0.187 | 0.200 |
|  | 8.072 | 5.015 | 6.719 | 3.587 | 6.355 | 5.436 | 6.373 | 4.313 | 7.539 | 8.598 | 8.350 | 10.807 | 10.675 | 9.915 | 9.032 | 8.877 | 7.991 | 8.286 |
| Nspouse | 0.240 | 0.146 | 0.253 | 0.104 | 0.115 | 0.038 | 0.174 | 0.033 | 0.082 | 0.056 | 0.080 | 0.122 | 0.120 | 0.139 | 0.098 | 0.102 | 0.088 | 0.081 |
|  | 4.624 | 2.942 | 4.827 | 2.192 | 2.491 | 0.841 | 3.709 | 0.731 | 2.414 | 1.706 | 2.484 | 3.935 | 3.673 | 4.110 | 2.852 | 2.974 | 2.691 | 2.566 |
| Private | -0.001 | 0.009 | -0.022 | -0.019 | -0.044 | -0.056 | -0.024 | -0.044 | -0.032 | -0.030 | -0.057 | -0.086 | -0.059 | -0.057 | -0.101 | -0.047 | -0.045 | -0.045 |
|  | -0.059 | 0.446 | -1.052 | -0.945 | -2.265 | -2.700 | -1.172 | -2.047 | -1.536 | -1.508 | -2.586 | -4.100 | -2.763 | -2.500 | -4.131 | -2.052 | -1.883 | -1.846 |
| South | -0.082 | -0.095 | -0.031 | -0.036 | -0.074 | -0.083 | -0.088 | -0.089 | -0.067 | -0.038 | -0.057 | -0.096 | -0.109 | -0.076 | -0.055 | -0.057 | -0.051 | -0.041 |
|  | -4.508 | -5.037 | -1.589 | -1.935 | -3.989 | -4.412 | -4.883 | -4.582 | -3.953 | -2.179 | -3.233 | -5.401 | -6.312 | -4.270 | -3.095 | -3.144 | -2.903 | -2.275 |
| City | 0.012 | 0.004 | 0.021 | 0.016 | 0.005 | 0.027 | -0.033 | 0.012 | 0.013 | 0.009 | 0.028 | 0.021 | -0.002 | -0.011 | 0.001 | -0.002 | 0.000 | -0.001 |
|  | 0.636 | 0.197 | 1.010 | 0.746 | 0.219 | 1.250 | -1.580 | 0.555 | 0.639 | 0.457 | 1.353 | 1.049 | -0.111 | -0.519 | 0.064 | -0.091 | -0.020 | -0.035 |


| N | 5,000 | 5,099 | 4,809 | 4,841 | 4,845 | 4,986 | 5,020 | 4,821 | 4,941 | 5,031 | 5,063 | 5,021 | 4,993 | 4,721 | 4,874 | 4,965 | 5,046 | 4,931 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| RSQ | 0.086 | 0.081 | 0.082 | 0.093 | 0.101 | 0.091 | 0.124 | 0.106 | 0.149 | 0.152 | 0.152 | 0.166 | 0.170 | 0.165 | 0.157 | 0.151 | 0.141 | 0.150 |

Spouse: Marital status dummy $=1$ if married, spouse present. Nspouse: Marital status dummy $=1$ if neither married with spouse present or never married.
Private: Class of worker dummy $=1$ if works for private firm or is self-employed. South: Region dummy $=1$ if south.
Ccity: Central city metropolitan statistical area status dummy $=1$ if central city.
IHS: Inc. High School, dummy $=1$ if Educ $<12$; IC: Inc. College, dummy $=1$ if $12<$ Educ $<16$; $\mathrm{C}+$ : College or more, dummy $=1$ if Educ $>=16$.

* t statistics.

Table 3. Correlation matrices of sample (cross-) moments

|  | $\mu_{10}$ | $\mu_{01}$ | $\mu_{20}$ | $\mu_{11}$ | $\mu_{02}$ | $\mu_{30}$ | $\mu_{21}$ | $\mu_{12}$ | $\mu_{03}$ |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\mu_{10}$ |  | -0.98 | 0.56 | -0.82 | 0.91 | -0.85 | 0.67 | -0.55 | 0.51 |
| $\mu_{01}$ | -0.98 |  | -0.50 | 0.79 | -0.91 | 0.80 | -0.66 | 0.59 | -0.54 |
| $\mu_{20}$ | 0.37 | -0.40 |  | -0.92 | 0.77 | -0.25 | -0.12 | 0.29 | -0.31 |
| $\mu_{11}$ | -0.79 | 0.82 | -0.84 |  | -0.96 | 0.50 | -0.18 | 0.04 | 0.00 |
| $\mu_{02}$ | 0.81 | -0.84 | 0.71 | -0.93 |  | -0.61 | 0.36 | -0.26 | 0.20 |
| $\mu_{30}$ | -0.93 | 0.87 | -0.27 | 0.68 | -0.68 |  | -0.90 | 0.72 | -0.66 |
| $\mu_{21}$ | 0.77 | -0.70 | -0.06 | -0.38 | 0.41 | -0.90 |  | -0.93 | 0.86 |
| $\mu_{12}$ | -0.76 | 0.71 | 0.10 | 0.36 | -0.31 | 0.82 | -0.91 |  | -0.97 |
| $\mu_{03}$ | 0.75 | -0.70 | -0.01 | -0.41 | 0.28 | -0.76 | 0.74 | -0.91 |  |

Above diagonal correlations for blacks and below for whites. Correlations of the sample moments used are in boxes.

Table 4. Estimated coefficients of the augmented log wage regression.

| Blacks |  | Whites |  | Blacks |  | Whites |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Constant | 0.6 | Constant | $\begin{array}{r} 1.4 \\ 12.65 \end{array}$ | X/100 | 0.58 | X/100 | 1.82 |
|  | 4.39 |  |  |  | 0.68 |  | 2.32 |
| Constant 1 | 22.37 | Constant 1 | $\begin{aligned} & 8.76 \\ & 1.16 \end{aligned}$ | X/100_1 | 263.69 | X/100_1 | 352.23 |
|  | 2.96 |  |  |  | 4.46 |  | 5.61 |
| Constant2 | 408.73 | Constant2 | $\begin{array}{r}539.2 \\ 4.52 \\ \hline\end{array}$ | X/100_2 | -3145.01 | X/100_2 | -5216.71 |
|  | 6.34 |  |  |  | -7.88 |  |  |
| IHS | -0.35 | IHS | -0.91 | X2/10000 | 2.32 | X2/10000 | -0.04 |
|  | -5.4 |  | -14.02 |  | 1.46 |  | -0.02 |
| IHS1 | 11.71 | IHS1 | 17.17 | X2_1 | -565.29 | X2_1 | -636.76 |
|  | 2.74 |  | 3.61 |  | -5.31 |  | -5.13 |
| IHS2 | -12.42 | IHS2 | 402.5 | X2_2 | 4323.32 | X2_2 | 6595.913.65 |
|  | -0.43 |  | 5.91 |  | 6.14 |  |  |
| IC | 0.47 | IC | 0.4 | Trend | 0.01 | Trend | $\begin{array}{r} -0.01 \\ -18.59 \end{array}$ |
|  | 6.73 |  | 7.37 |  | 1.86 |  |  |
| IC1 | -15.19 | IC1 | -18.08 | Spouse | 0.2 | Spouse | 0.22 38.97 |
|  | -2.76 |  | -3.72 |  | 32.3 |  | 38.97 |
| IC2 | -75.52 | IC2 | 8.35 | Nspouse | 0.1 | Nspouse |  |
|  | -1.85 |  | 0.11 |  | 12.29 |  | 15.05 |
| C+ | 0.65 | C+ | 1.17 | North | -0.07 | North | -0.03 |
|  | 8.01 |  | 21.49 |  | -16.18 |  |  |
| C+1 | -2.41 | C+1 | -26.58 | South | -0.22 | South | -0.1 |
|  | -0.39 |  | -5.57 |  | -60.6 |  | -33.07 |
| C+2 | -277.56 | C+2 | -425.76 | City | 0.07 | City | 0.03 |
|  | -6.21 |  | -5.7 |  | 18.19 |  | 7.59 |


| n | 104,648 | n | 167,190 |
| :---: | :---: | :---: | :---: |
| r2 | 0.13 | r2 | 0.1 |

t statistics calculated using White standard errors are presented.
IHS: Inc. High School, dummy $=1$ if Educ <12.
IC: Inc. College, dummy $=1$ if $12<$ Educ $<16$.
C+: College or more, dummy $=1$ if Educ $>=16$.
X : Potential experience.
Spouse: Marital status dummy $=1$ if married, spouse present.
Nspouse: Marital status dummy = 1 if neither married with spouse present or never married.
Private: Class of worker dummy $=1$ if works for private firm or is self-employed.
South: Region dummy = 1 if south.
City: Central city metropolitan statistical area status dummy $=1$ if central city.


Table 5. Estimated coefficients of the standard log wage regression by FIML


Table 5. Estimated coefficients of the standard log wage regression by FIML (Continuation)
Black Males


Table 5. Estimated coefficients of the standard log wage regression by FIML (Continuation) No, N1, N2: Number of men not working, working and earning less than $\$ 50000$ (dolars of 1981 ) a year, and working and eaming more than $\$ 50000$ a year
$* \mathrm{t}$ statistics. IHS: Inc. High School, dummy $=1$ if Educ <12; IC: Inc. College, dummy $=1$ if $12<$ Educ $<16 ; \mathrm{C}+$ : College or more, dummy $=1$ if Educ $>=16$.
Hunder 18: Number of persons in household under age 18. Private: Class of worker dummy $=1$ if works for private firm or is self-employed. South: Region dummy $=1$ if south
Ccity: Central city metropolitan statistical area status dummy $=1$ if central city.





Figure 1: Effect of changes in $\sigma_{e}^{2}$ on equilibrium outcome. (This is equivalent to changes in the signal to noise ratio in the labor market)


Figure 2: Effect of $\sigma_{b}^{2}$ on equilibrium outcome.


Figure 3: Effect of changes in degree of concavity of schooling tehnology on equilibrium outcome.


Figure 4: Phase diagram in case of adaptive expectations


Figure 5: Illustration of case $(i),(i i)$ and (iii) in proposition 2.

Figure 5.A
Multiplicity of equilibria with sigmab2>0


Figure 6
Decomposition of log wage differential for standard model. OLS



Figure 7: Distribution of education levels for black males, 1964-1988 ${ }^{1}$.

[^11]

Figure 8: Distribution of education levels for white males, 1964-1988².

[^12]

Figure 9: Distribution of experience levels for black males, 1964-1988.


Figure 10: Distribution of experience levels for white males, 1964-1988.

Figure 11
Decomposition of log wage differential for augmented model. OLS


Figure 12
Decomposition of log wage differentials for standard model. FIML


Figure 13
Decomposition of log wage differentials for standard model. FIML vs OLS



[^0]:    *Correspondence: New York University, Department of Economics, 269 Mercer Street, 7th floor, NY, NY 10003, USA. Fax: +1 21299541 86. E-mails: medina@econ.nyu.edu, hobijnb@econ.nyu.edu. Webpage Bart Hobijn: http://pages.nyu.edu/~bh32. This article can be downloaded from: http://pages.nyu.edu/~ cam2319/cfailure.html

[^1]:    ${ }^{1}$ This functional form is a generalization of that used by L\&S and Lundberg (1992), whose assumptions basically imply that $S_{i}\left(e_{i}\right)=2 e_{i}^{1 / 2}+b_{i}$.
    ${ }^{2}$ Independence of $a_{i}$ and $b_{i}$ is simply assumed for convenience and does not influence the results below. That is, the same results can be derived assuming there is some correlation between someone's initial talent and her subsequent learning abilities.

[^2]:    ${ }^{3}$ The equilibria derived in this paper are subgame perfect equilibria, where in each stage of the game we limit our focus on pure strategy Nash equilibria.

[^3]:    ${ }^{4} \mu_{b}$ is assumed to be equal for both groups throughout this section. Furthermore, in our numerical examples that follow below we assume $\mu_{a}=\gamma^{\gamma}-\frac{1}{2} \sigma_{a}^{2}$, which implies the normalization $E\left[\frac{a_{i}}{\gamma^{\gamma}}\right]=1$

[^4]:    ${ }^{5}$ One possibility pointed at by Arrow (1973) is based on the theory of cognitive dissonance as developed by Festinger (1957). Under this view, if individuals discriminate, they might justify such action by subjectively assigning beliefs to the two groups involved, so that his action of discriminating becomes justified by such beliefs.

[^5]:    ${ }^{6}$ Kremer (1993) uses Cooper and Johns' analysis to illustrate a strategic complementarity in a model of statistical discrimination caused by a complementarity in the production technology. In Moro and Norman (1996) the technology also exhibits complementarities.

[^6]:    ${ }^{7}$ Each figure considers a change from the benchmark case: $\sigma_{a}^{2}=0.06, \sigma_{b}^{2}=0.06$,

[^7]:    ${ }^{8}$ The data used in this paper for the period 1964-1988 were made available by the Inter-University Consortium for Political and Social Research and were originally collected by Mare and Winship (1990). Data for the period 1989-1998 can be found at ftp://elsa.berkeley.edu/pub/cps/march_suppl/data/

    Neither the collectors not the ICPSR bear any responsibility for the analysis presented here.
    ${ }^{9}$ Since before 1976 weeks worked per year are not available, we use the information available about the worker being a full or part year worker to assign different number of weeks a year to these two groups.
    ${ }^{10} \mathrm{We}$ also include a vector of control variables, such as dummy variables for marital status, class of worker (working for a public firm or not), region where he lives and central city metropolitan statistical area status. See the tables for a detailed description.

[^8]:    ${ }^{11}$ For example, the survey does not allow to distinguish high school graduates from recipients of a General Equivalence Certificate-GED-. In particular, Cameron and Heckman (1993) find that earnings of GED recipients is comparable to that of high school dropouts,

[^9]:    which will contribute to increase the wage differential for high school graduates in our sample.

[^10]:    ${ }^{12}$ Since in a previous exercise perfomed with (cross)-moments of the first, second and third order we got a poor result due to multicollinearity, we estimate the model with only (cross)-moments of second order.

[^11]:    ${ }^{1}$ Years of education are gotten from substracting one year to the level shown in the figure, i.e. to get the relative frequency of men with 12 years of education, read people with 13 years of education in the figure.

[^12]:    ${ }^{2}$ Years of education are gotten from substracting one year to the level shown in the figure, i.e. to get the relative frequency of men with 12 years of education, read people with 13 years of education in the figure.

